

Optimization of a Spherical Parallel Manipulator for Enhanced Performance in Human-Centric Environments

ME6103 Final Project, Spring 2025

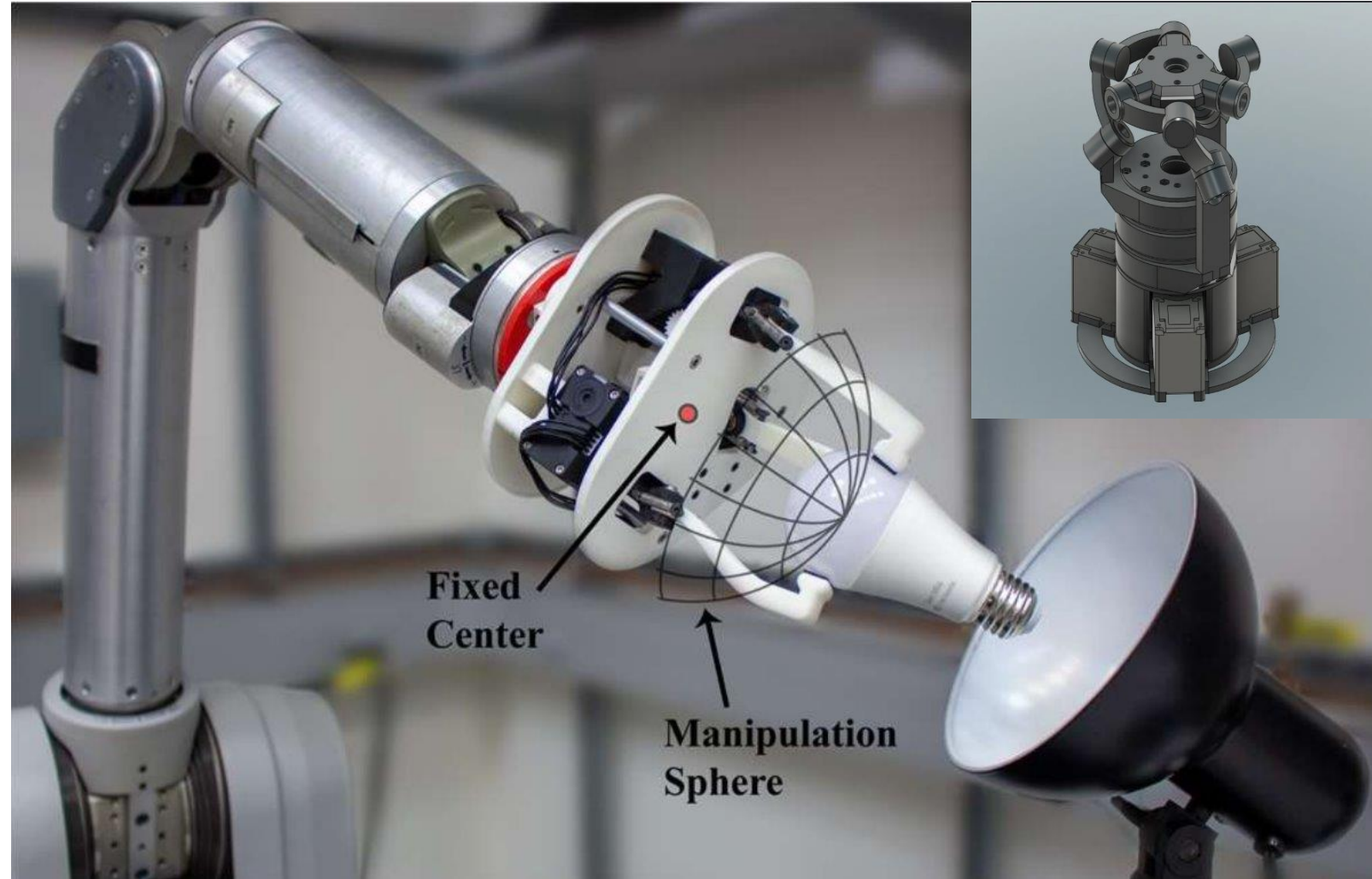
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Nina Latorre, Shubh Raval



Introduction

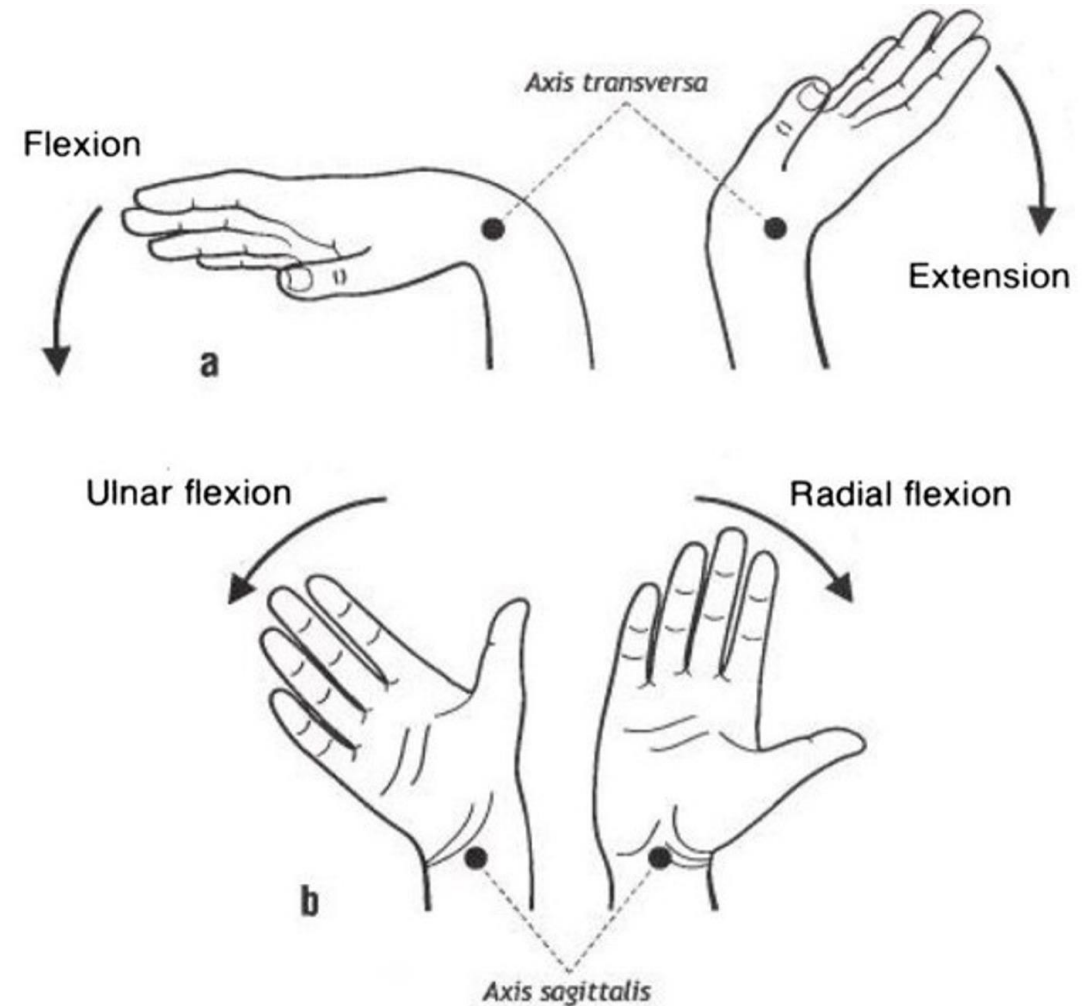
What is a Spherical Parallel Manipulator?

- A spherical Parallel Manipulator is a type of parallel robot with 3 degrees of rotational freedom
- Effectively this allows it to rotate around a fixed center point
- This simple attachment can make a standard collaborative robot incredibly more dexterous
- The tools presented in this course provide an excellent means of analyzing the many parameters of this robot and optimize an initial concept design

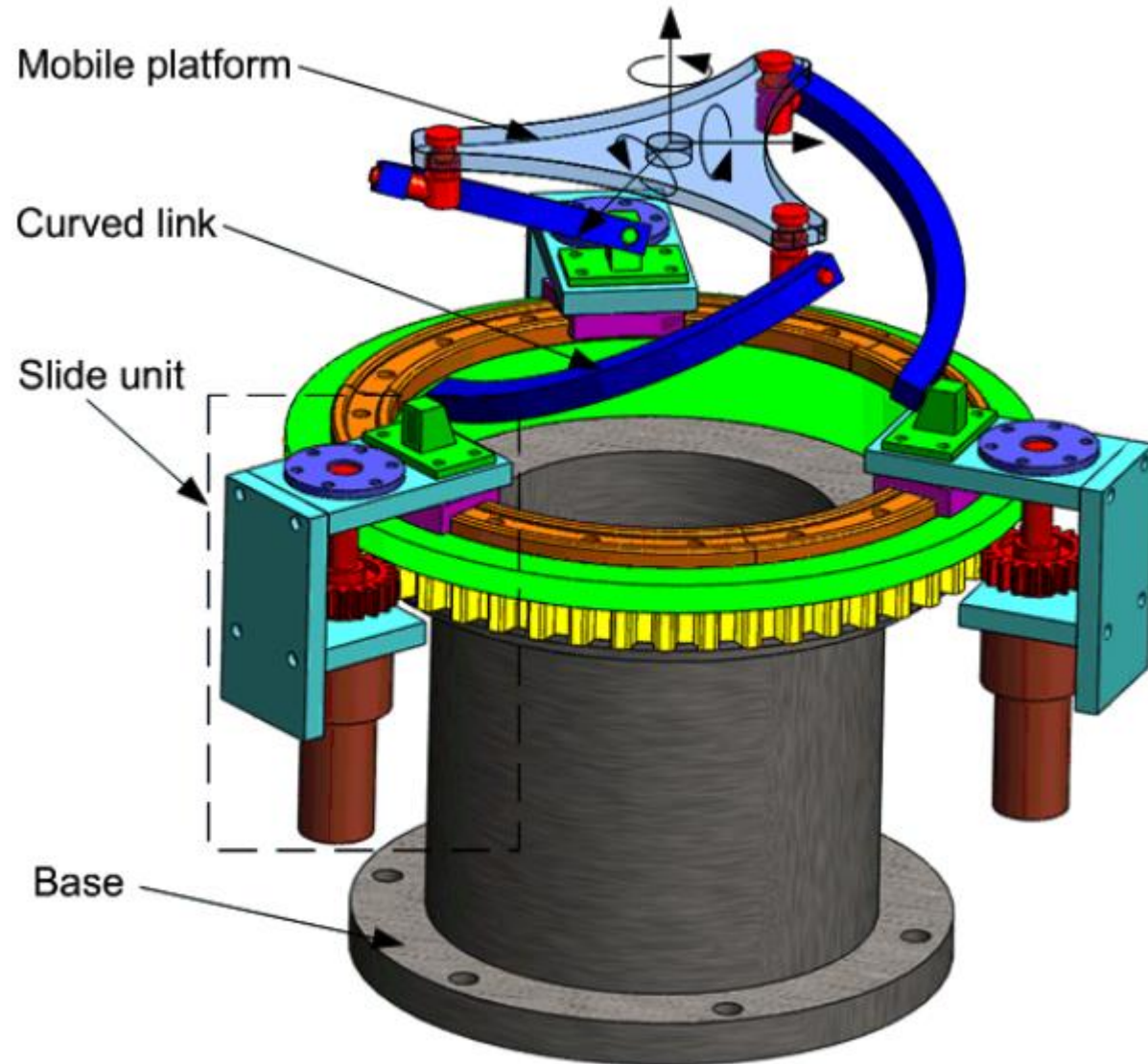


Point of Reference

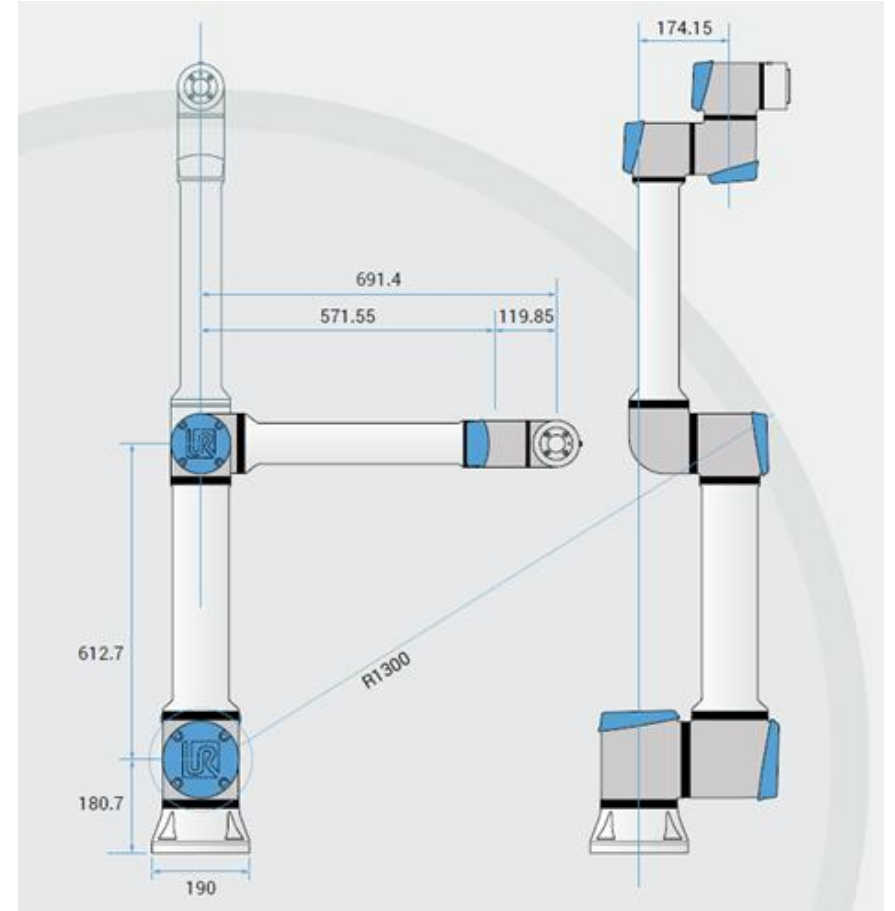
- The human wrist effectively serves as an immediate comparison of what the mechanism can achieve
- However rather than being limited in a direction such as ulnar flexion the SPM can achieve large rotation in all directions
- With robots being more prevalent in human centric environments excellent dexterity and orientation adjustment without needing to have large robot repositions is paramount



Reference Design



UR10 Cobot Arm



Optimization Goals

Minimize:

$$f_1(\bar{x}) = 3(m_{actuator} + m_{linkage})$$

$$f_2(\bar{x}) = -GCI$$

Subject to:

$$\delta_{linkage} \leq 0.5\text{mm}$$

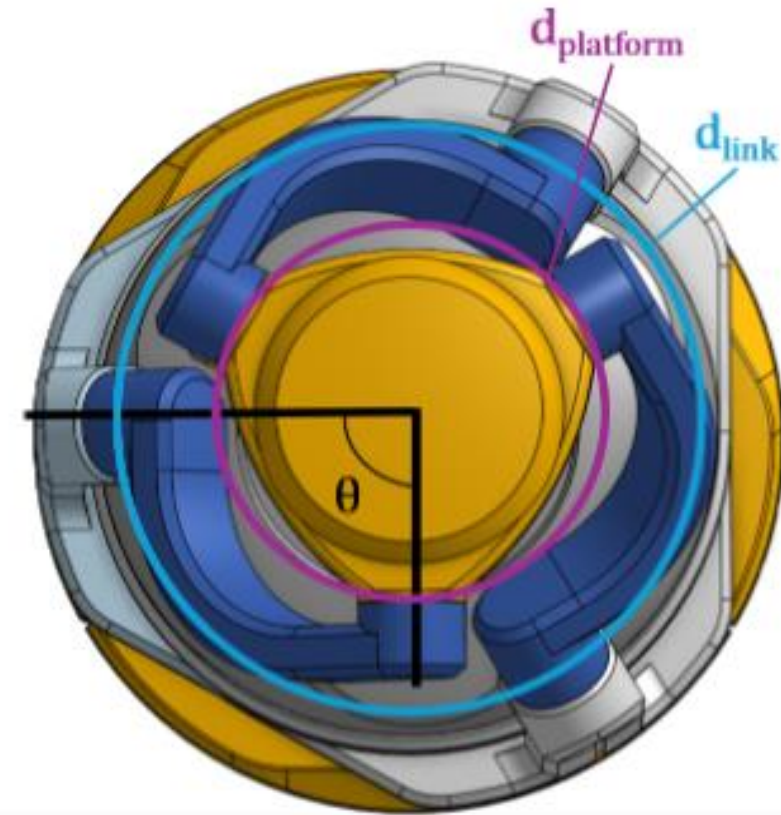
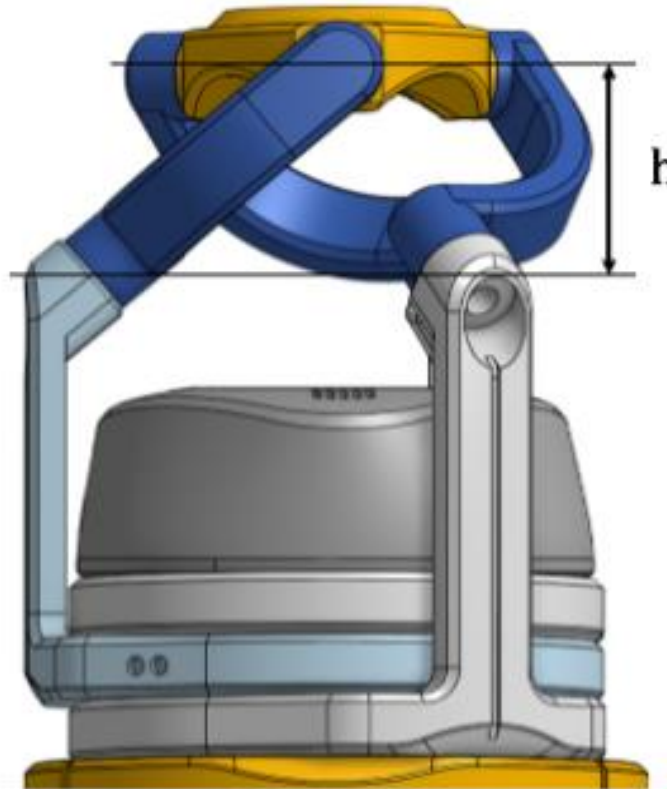
$$\tau_{actuator} \geq 2\tau_{min}$$

$$10\text{mm} \leq h \leq 100\text{mm}$$

$$30^\circ \leq \theta \leq 150^\circ$$

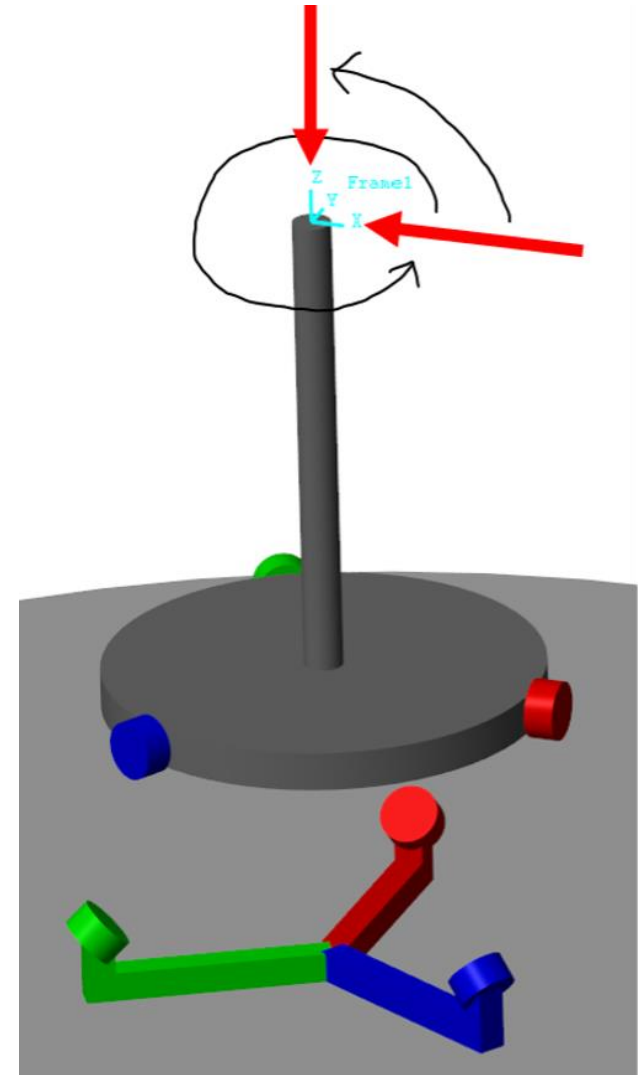
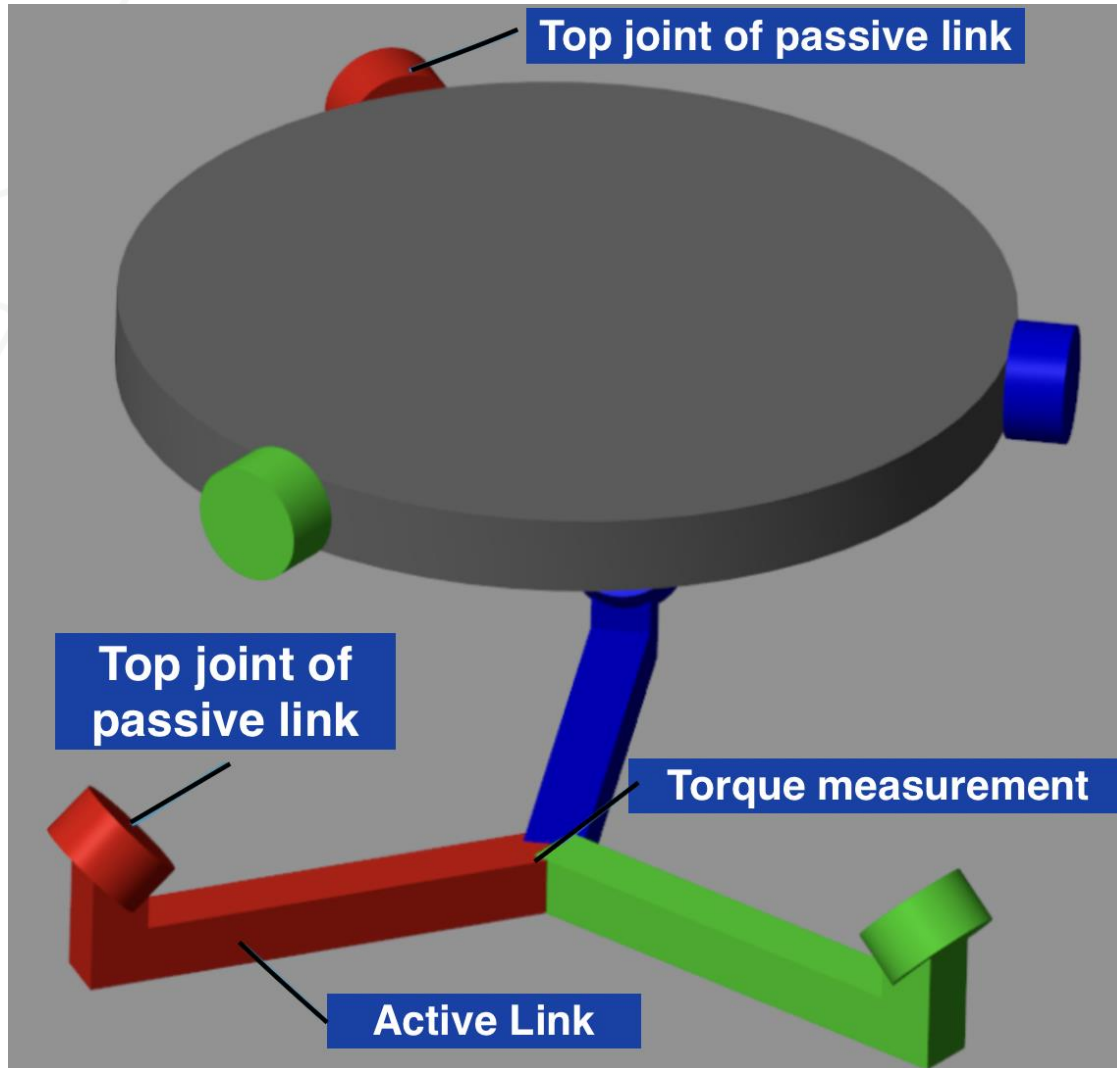
$$95\text{mm} \leq d_{platform} \leq 125\text{mm}$$

$$d_{link} = 90\text{mm}$$

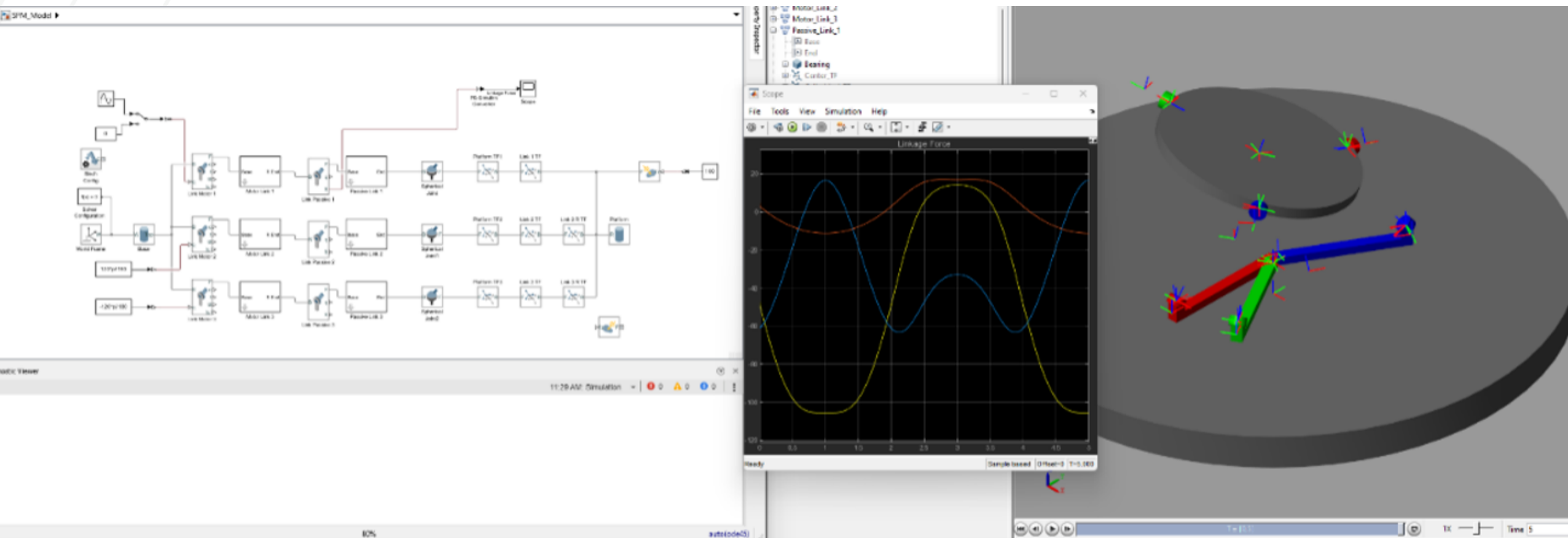


Methods

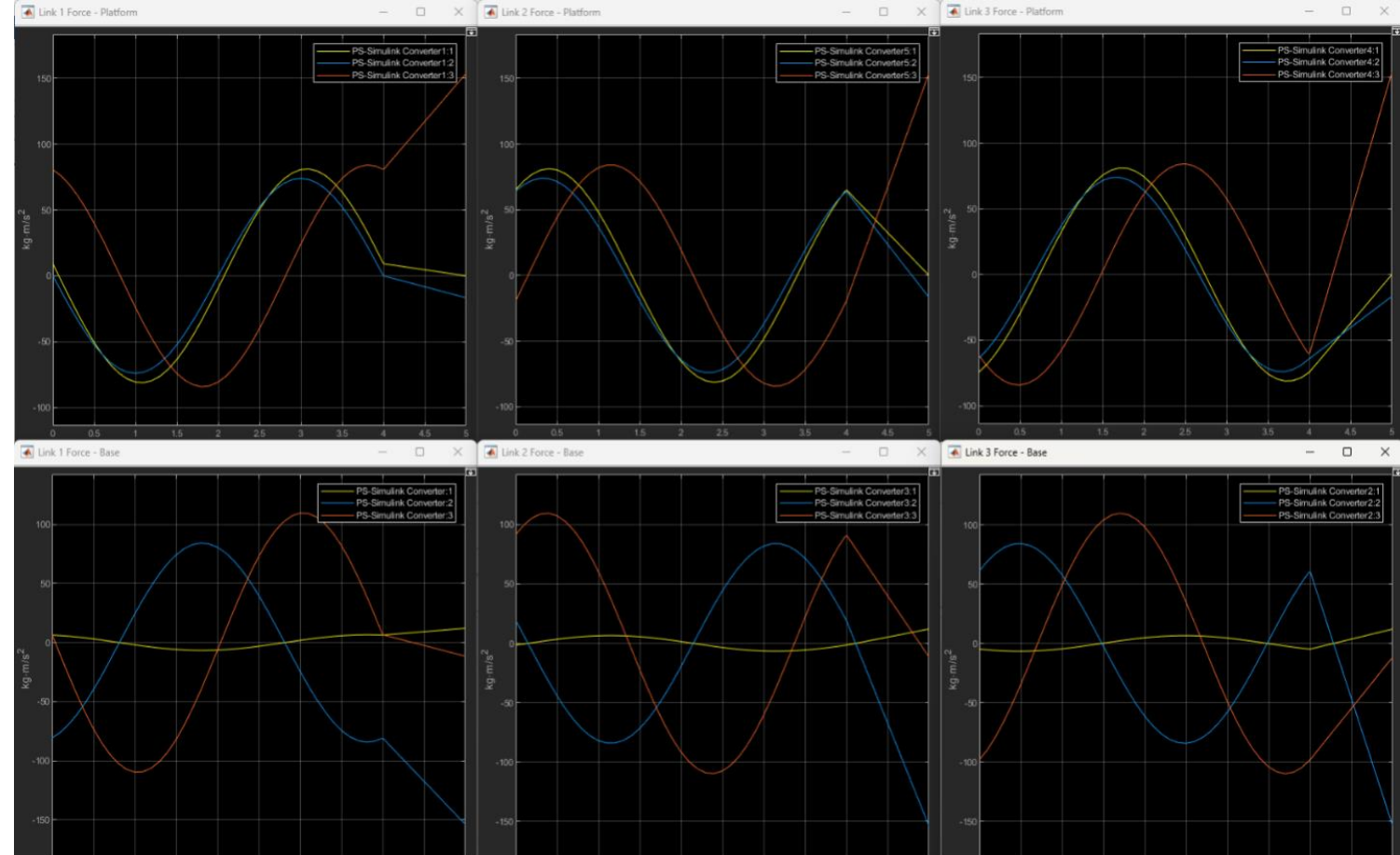
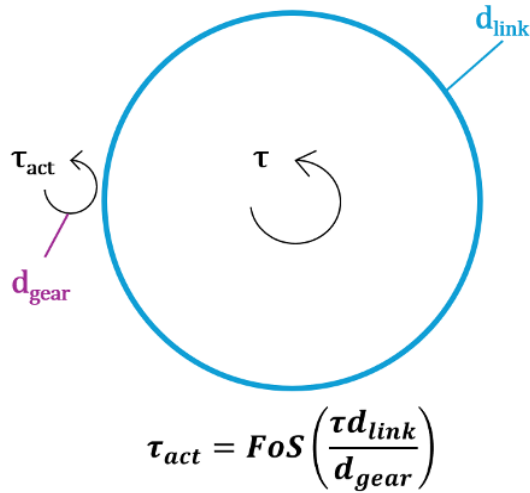
Design Space & Problem Formulation



Simulink Model

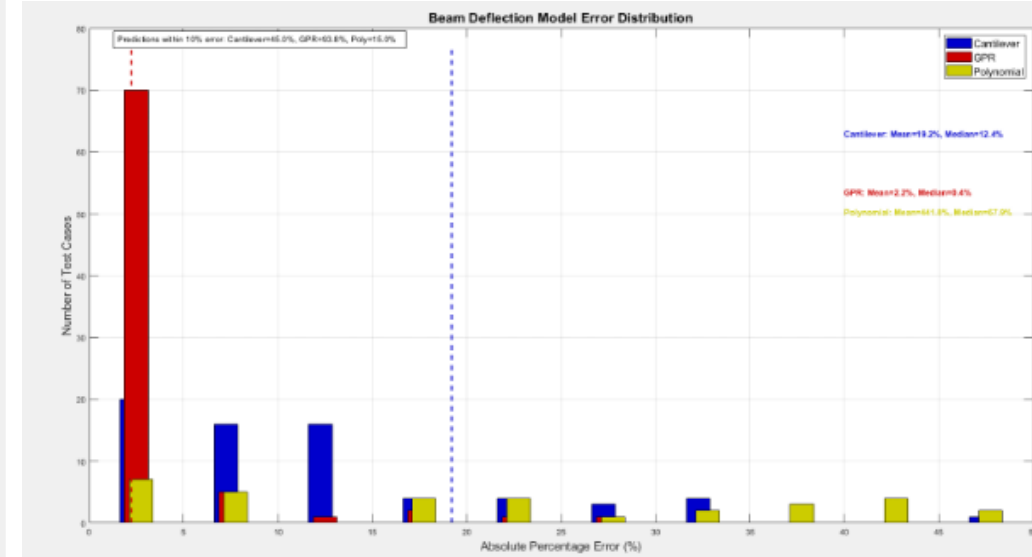
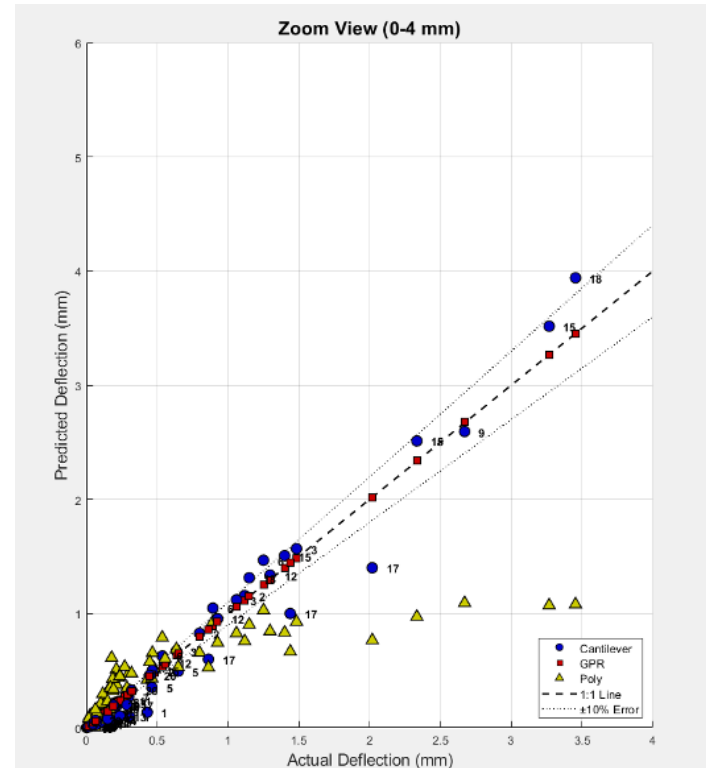
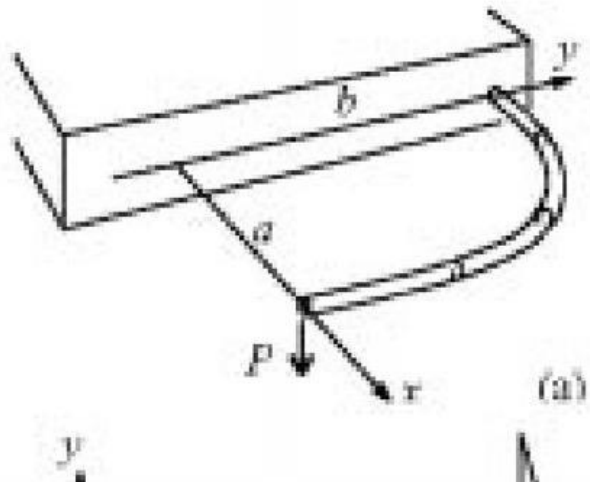
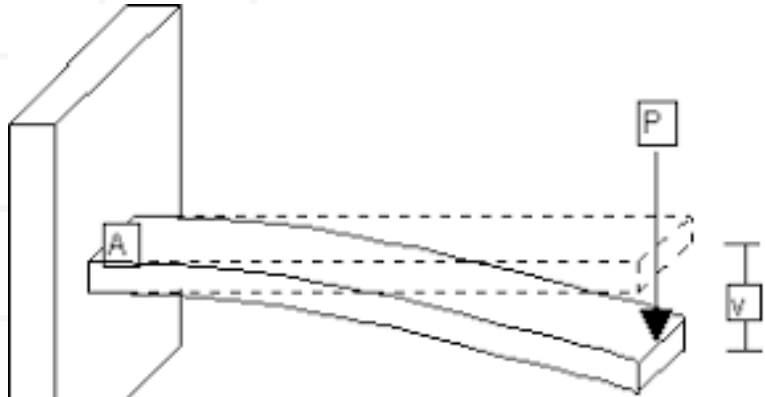


Actuator Selection



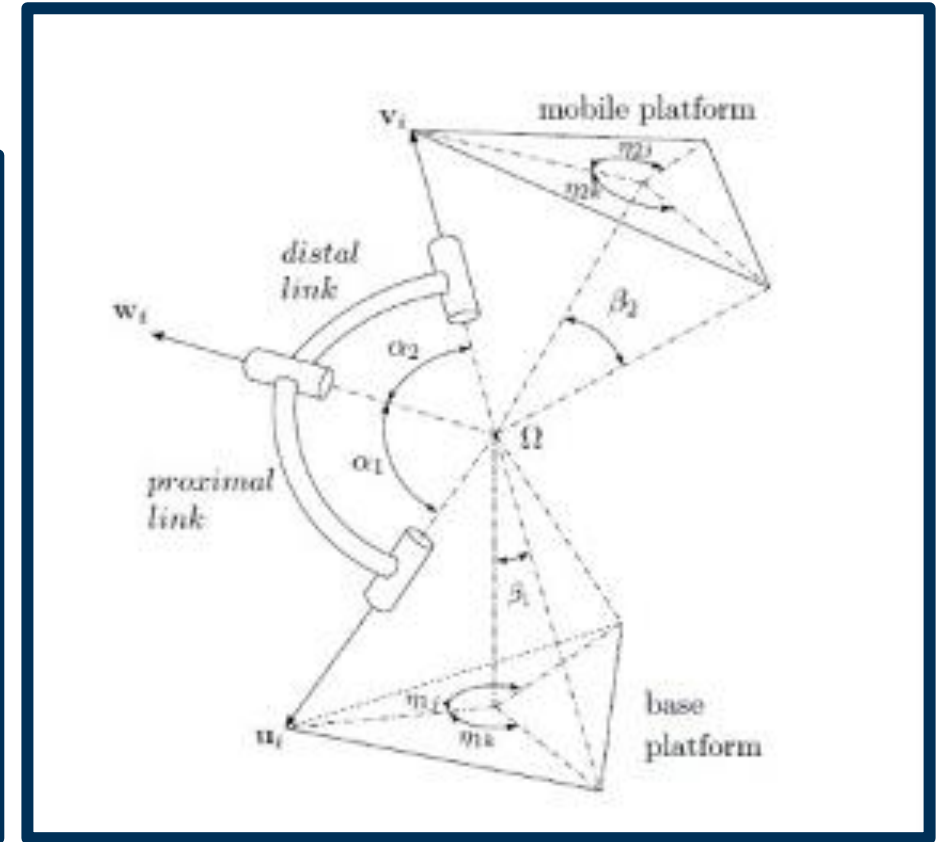
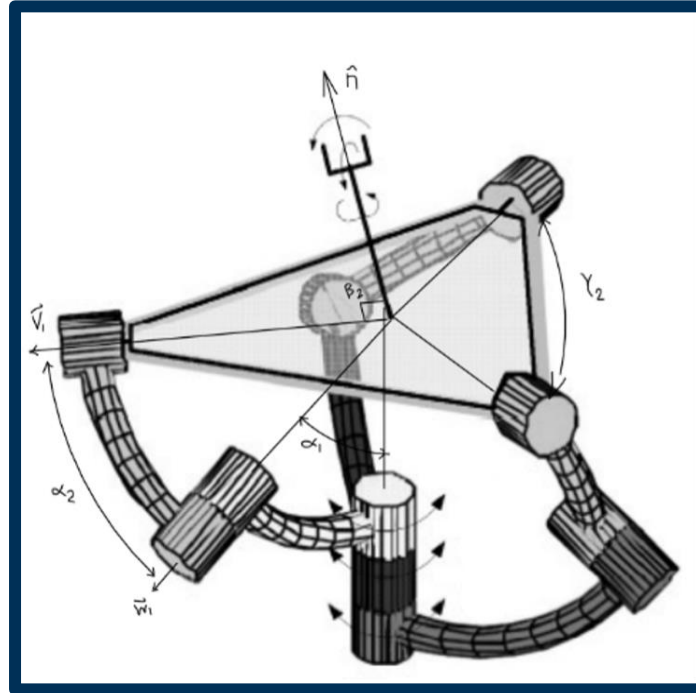
Part Number	Manufacturer	Motor Type	Rated Torque (Nm)	Max Torque (Nm)	Max Speed (rpm)	Diameter (mm)	Mass (g)	Torque Density (Nm/kg)	Cost
GL30 KV290	CubeMars	BLDC	0.080	0.280	2200	43	41	6.829268293	\$ 55.99
GL35 KV100	CubeMars	BLDC	0.150	0.460	815	50	90	5.111111111	\$ 54.99
GL40 KV70	CubeMars	BLDC	0.250	0.730	600	46.5	107	6.822429907	\$ 91.90
RMD-L-4015 20T	MyActuator	BLDC Servo	0.220	0.490	1010	40	120	4.083333333	\$103.00
722-401	Precision Micro Drives	BLDC	0.029	0.252	16380	22	122	2.062622951	\$ 88.57
RMD-L-5010 35T	MyActuator	BLDC Servo	0.260	0.650	1015	50	135	4.814814815	\$175.45
RO60 KV115-Lite	CubeMars	BLDC	0.800	2.400	5520	60	195	12.30769231	\$ 77.90
G006984	iPower Motor	BLDC	0.392	0.392	400	60	207.8	1.887184133	\$ 54.44
GL60 KV25	CubeMars	BLDC	0.600	1.750	516	69	230	7.608695652	\$136.90
RO60 KV115	CubeMars	BLDC Servo	0.800	2.400	5520	60	248	9.677419355	\$ 85.90
R60 KV115	CubeMars	BLDC	0.75	2.3	4150	60	248	9.274193548	\$177.90
AKE60-8 KV80	CubeMars	BLDC Servo	5.000	12.500	240	60	260	48.07692308	\$272.90
RB-Blu-303	Blue Robotics	BLDC	0.500	0.500	9400	40	282	1.773049645	\$160.00
RMD-X4 1:6	MyActuator	BLDC Servo + Gearbox	1.200	1.200	600		300	4	\$250.00
36PG-3650BL-14 12V	E-S Motor	BLDC + Gearbox	0.392	0.392	290	36	450	0.871459695	\$ 42.50
36PG-3650BL-14 24V	E-S Motor	BLDC + Gearbox	0.784	0.784	570	36	450	1.74291939	\$ 42.50
AKE80-8 KV80	CubeMars	BLDC Servo	12.000	30.000	570	80	570	52.63157895	\$339.90
DCM4112	Phidgets	BLDC Servo	0.490	0.490	4000	57	4000	0.12254902	\$ 83.44

Linkage Deflection Model and Validation



Kinematic Formulation

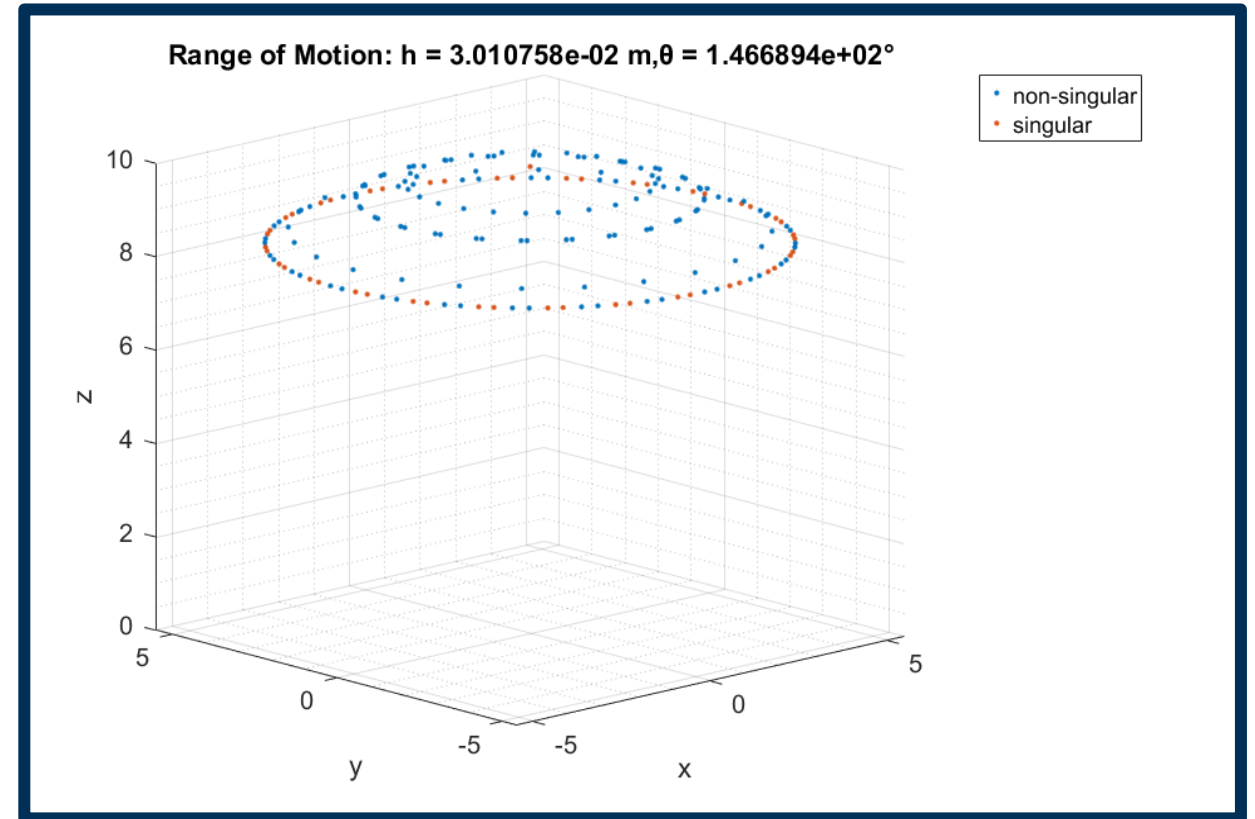
- Global Conditioning Index
 - Dexterity of System
 - Range of Motion
- Formulation Validation
 - Results less than 1% difference between various research papers



Kinematic Formulation

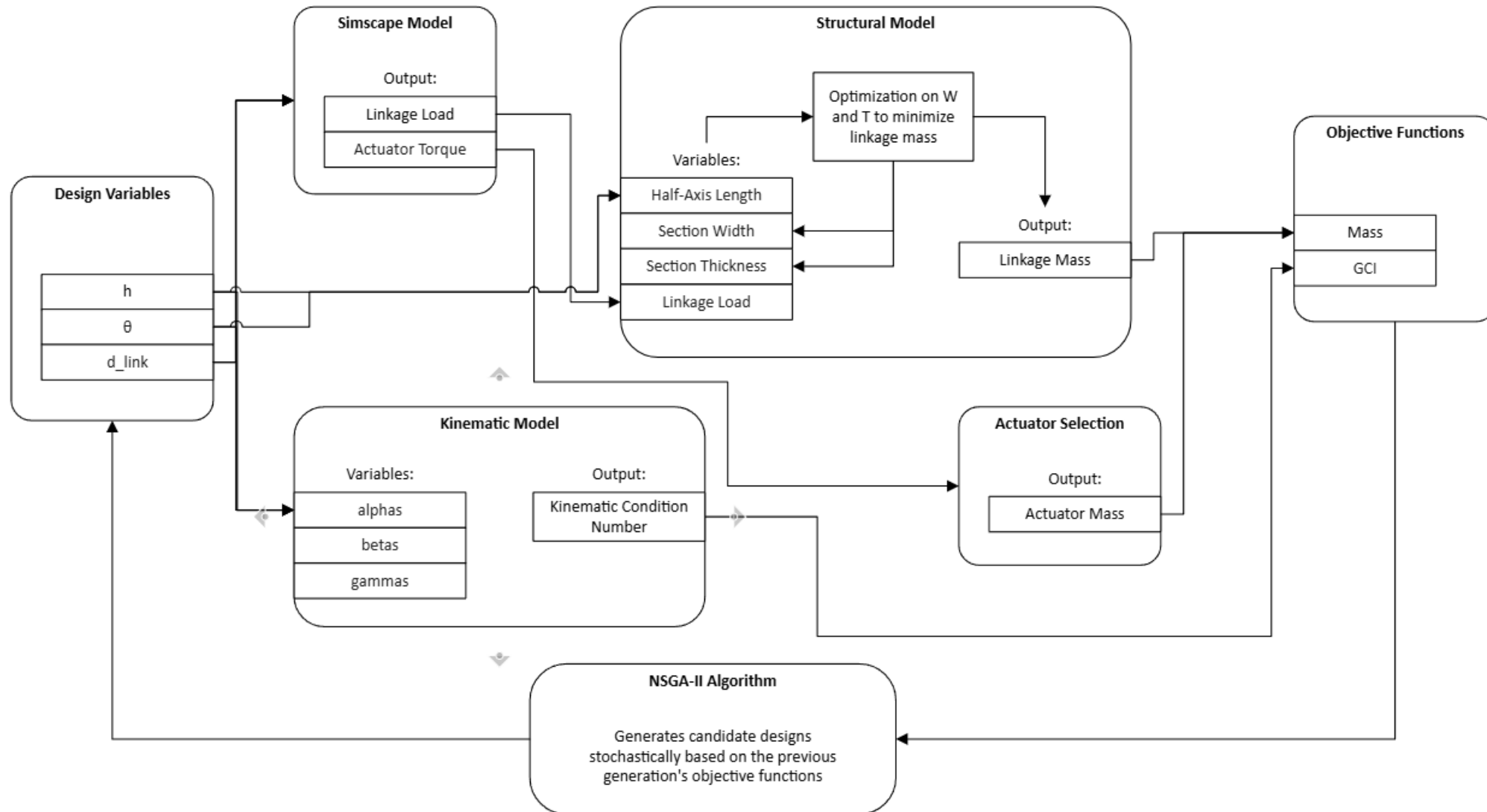
Optimal Workspace

- What determines the controllability of our SPM?
- Difference between singular and non-singular points



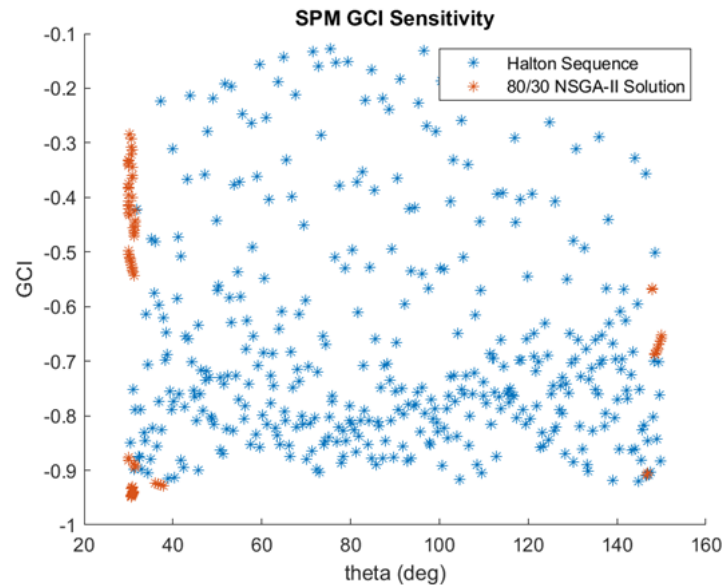
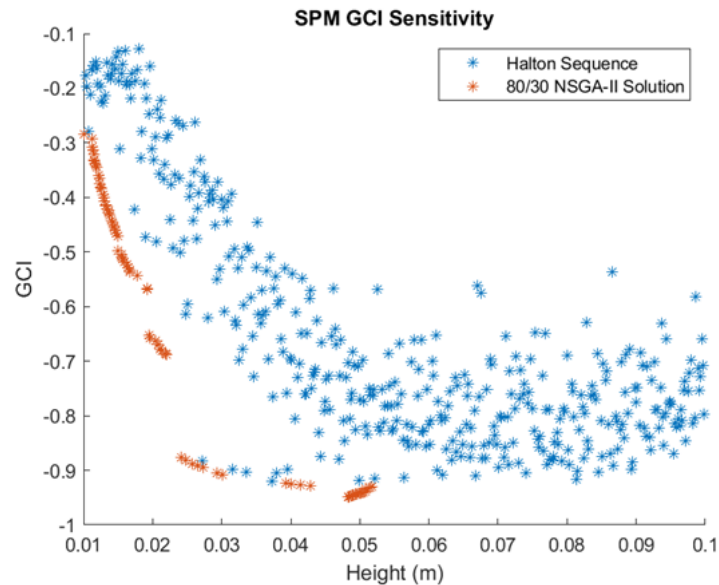
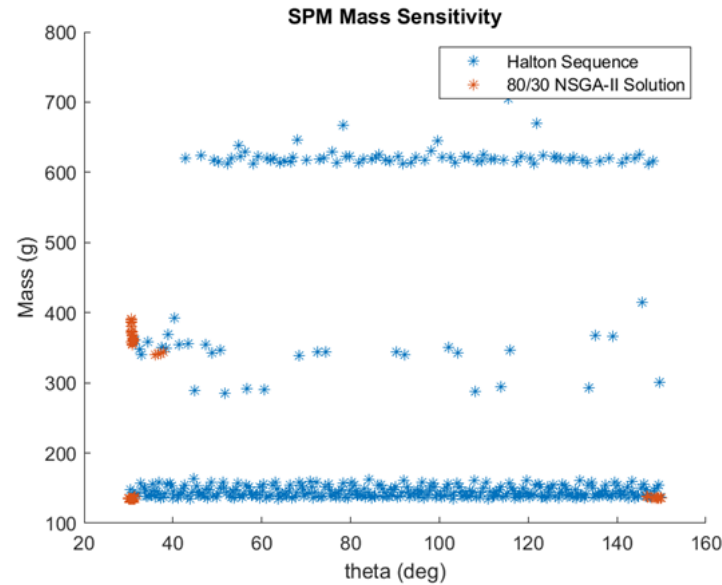
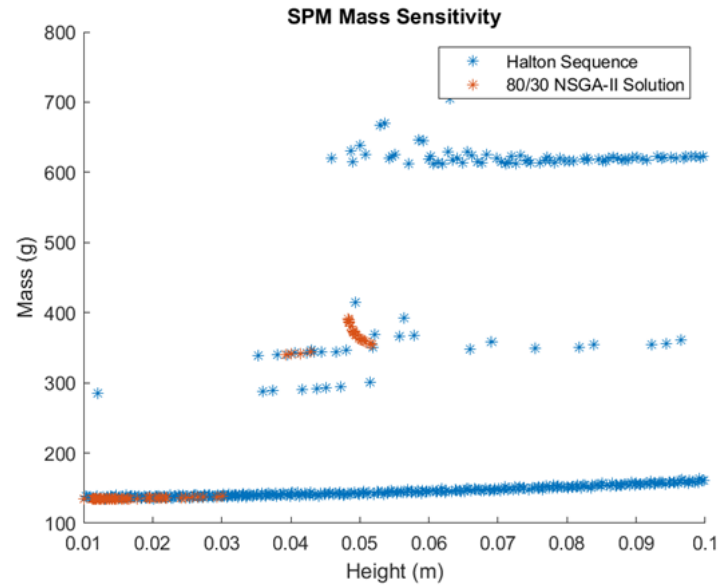
Optimization Architecture

Analysis Methods & Results

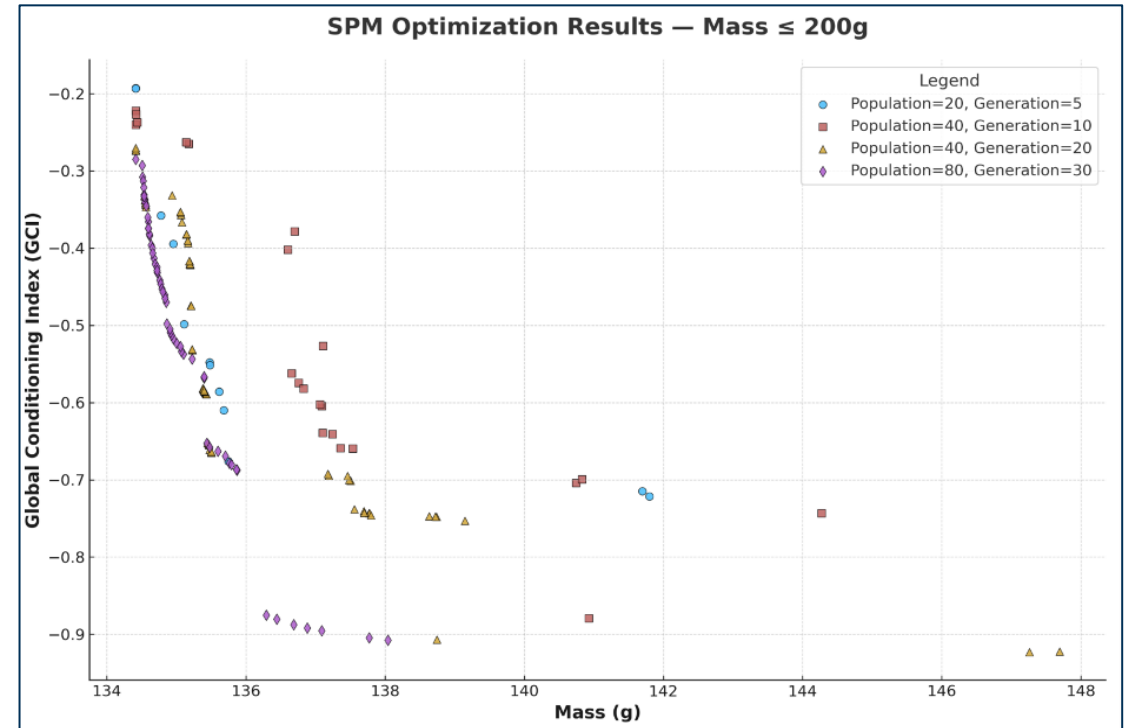
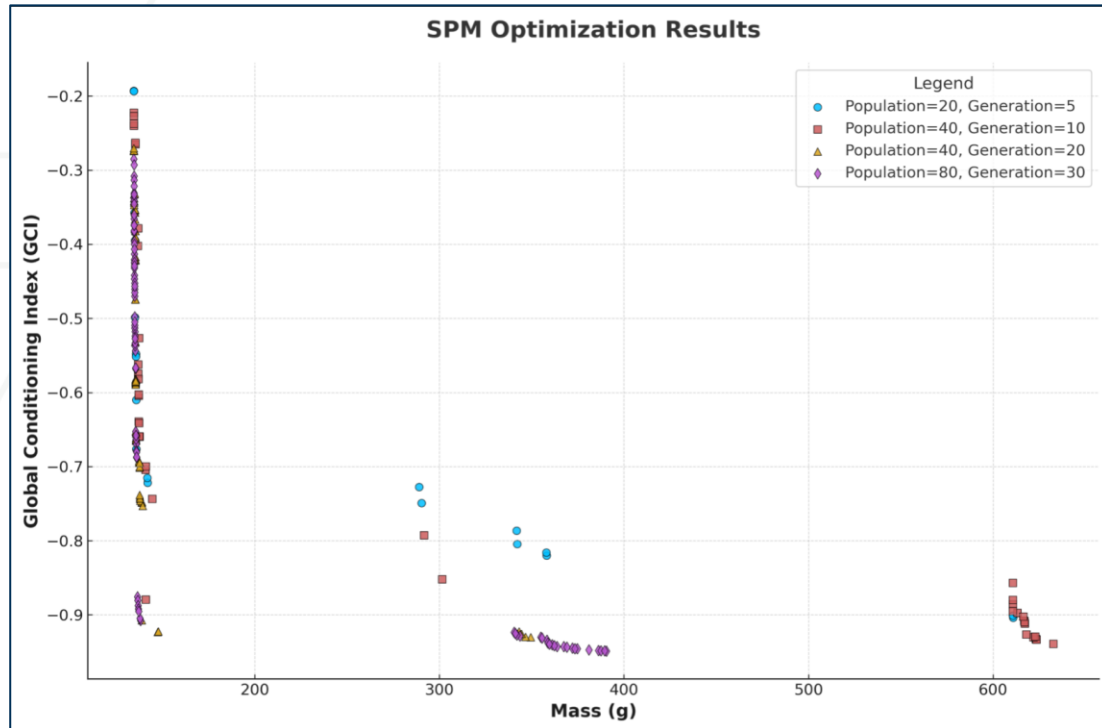


Final Results and Conclusion

SPM NSGA-II Solutions and Halton Design Space Exploration



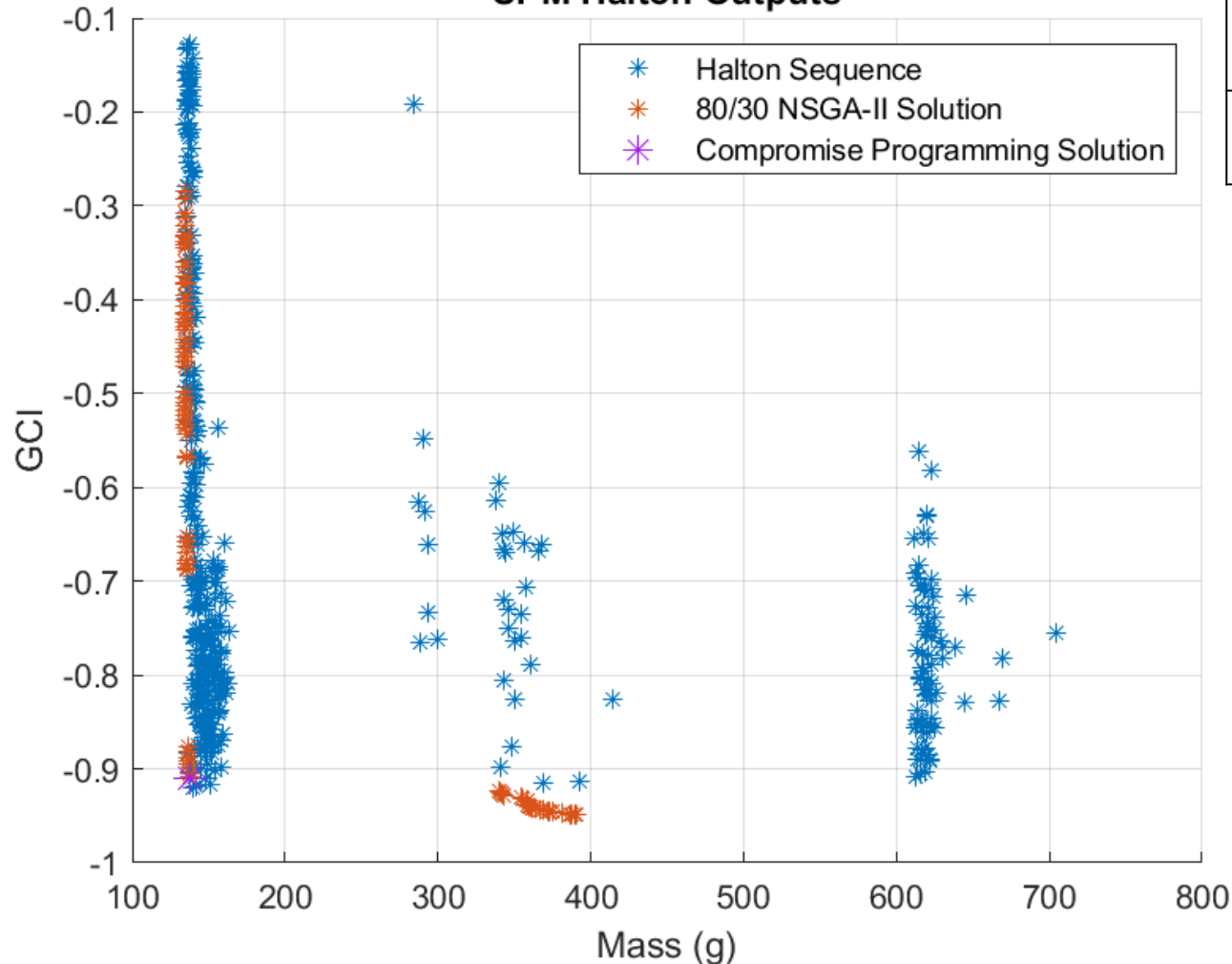
Combined Solutions from NSGA-II trials



Optimal Solution				
GCI	Mass (g)	Height (mm)	Theta (deg)	Base Diameter (mm)
0.91	138	30	146.68	96

Optimal Solution

SPM Halton Outputs

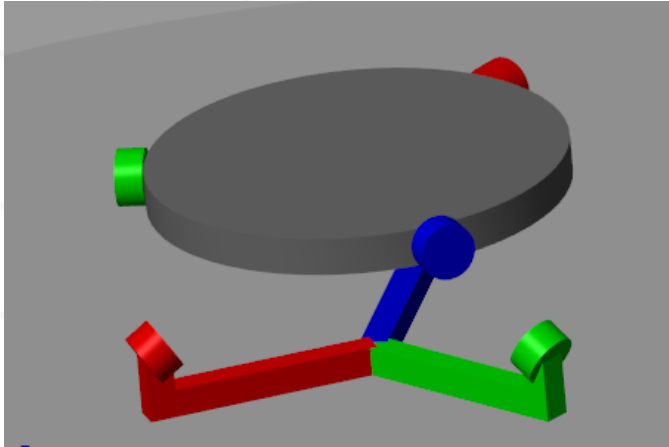


Optimal Solution

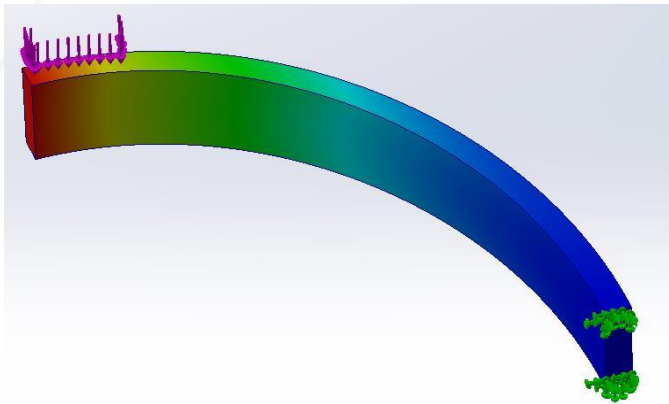
GCI	Mass (g)	Height (mm)	Theta (deg)	Base Diameter (mm)
0.91	138	30	146.68	96

- **Actuator Discontinuities:** Pareto front breaks stem from discrete actuator choices; mass jumps occur when switching to higher-torque motors, guiding selection near transition points.
- **Dexterity–Mass Tradeoff:** Higher GCI requires stiffer, heavier linkages to handle torque, linking dexterity gains to structural mass increases.
- **Modeling Insights:** Despite simplified deflection and collision assumptions, adding base diameter as a variable and actuator discreteness yielded mass-efficient, high-GCI designs validated in Simulink.

Optimal Solution Breakdown



Optimized SPM Model Represented in Simulink



Optimized SPM Linkage with Dimensions:

$a = 45 \text{ mm}$

$b = 56.6 \text{ mm}$

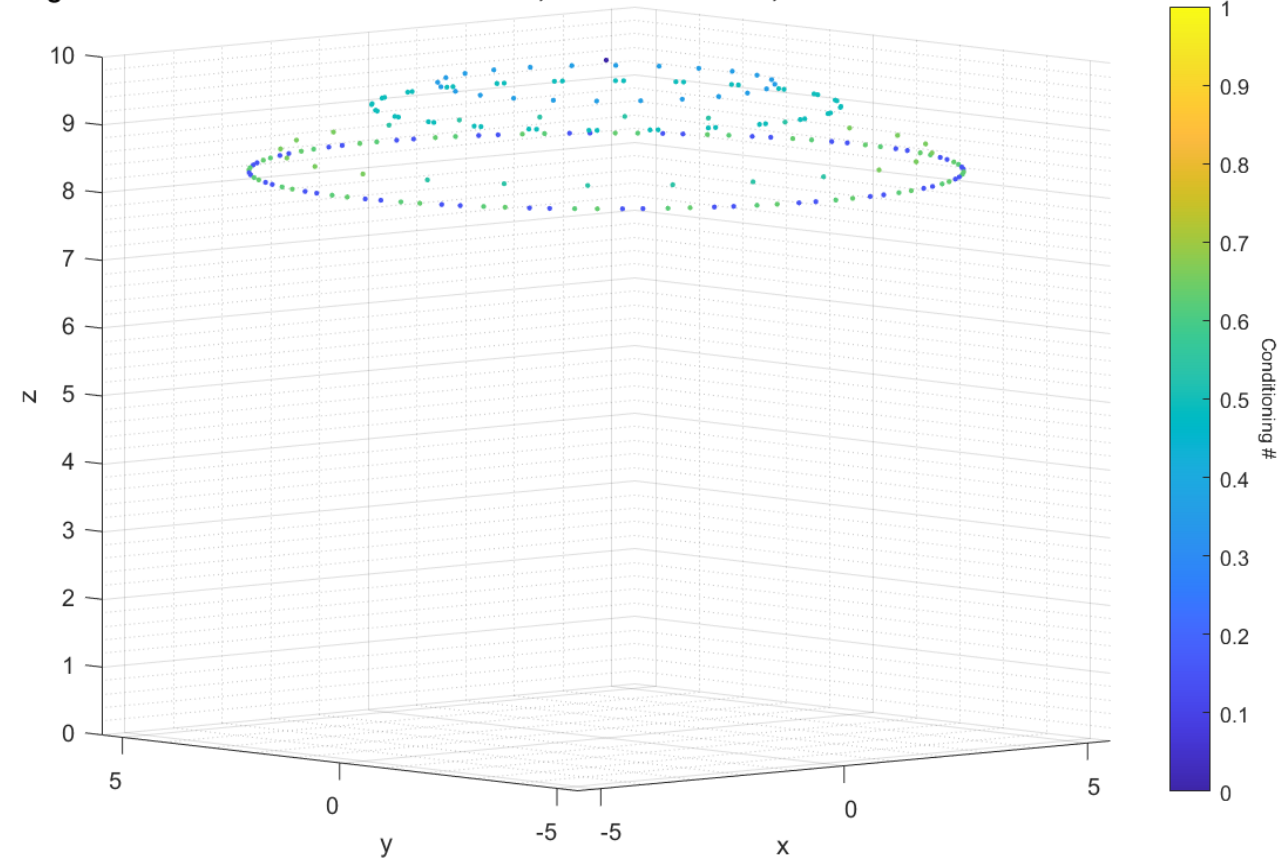
Width = 3 mm

Thickness = 10 mm



Chosen Actuator of CubeMars
GL30 KV290

Range of Motion w/ GCI: $h = 3.010758\text{e-}02 \text{ m}$, $\theta = 1.466894\text{e+}02^\circ$, Base Diameter = $9.601612\text{e+}01 \text{ mm}$



Workspace of Optimized SPM

Conclusion

Lessons Learned

- Successfully scoped a complex design problem by simplifying where needed, allowing us to explore meaningful trends within project constraints.
- Gained hands-on experience with optimization tools like NSGA-II, building confidence in applying genetic algorithms to real engineering systems.
- Learned the importance of model fidelity—simple, fast approximations were key to balancing deflection, mass, and kinematic accuracy.
- Future work could include multi-pose load cases, refined linkage design, and physical prototyping to validate and extend our results.
- Exploring neural networks or surrogate models could accelerate evaluation time and enable deeper optimization, especially with discrete choices.

Future Prospects

- Consider a variety of load cases
- Manufacture of a physical prototype for comparison
- Training more complex models such as neural networks