Optimization of a Lightweight and Stable Structure for a Wearable Blooming Flower Mechanism

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Photo by Aaron Goldgewert. Model: Aliza Feffer. Designer: Maia Hirsch.
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Abstract

This project addresses the structural optimization of a support structure for a wearable. This structure is designed to support a set of petals that bloom when a motor is activated. The challenge addressed is to optimize the beam's length, height, and material properties in order to minimize torque, defection and weight. For this, the problem is approached by analyzing a static and a dynamic force to simulate the physical behavior of the beam under gravity and the walking of the wearer. This project also compared the performance of two materials, PLA and PETG, in terms of beam deflection. CVX is used to optimize the results on material, and beam dimensions.

Introduction

Wearable robotics is an emerging field in the fashion industry that combines aesthetics with functionality, bringinging engineers and designers to collaborate closely. One of the main issues of this field is how to design components that are light and capable of performing the required mechanical tasks, while being wearable at the same time. The focus of this project is on optimizing the beam structure that supports the 'blooming flower' mechanism on a dress. The optimization process minimizes torque, deflection and weight, considering material choices as well as dynamic forces resulting from the user's movement.

Specifically, research in soft robotics has explored the integration of robotics into wearable, being soft robots compatible with fabrics, allowing for the creation of flexible and adaptable wearable devices. Pneumatic actuator research has shown the potential of mounting wearable robots into the human body, while being lightweight and aiding to perform complex movements, shedding light on the importance of structural optimization in wearable robotics **[1]**. Material science plays a crucial role in this field, as the choice of materials directly impacts the performance and comfort of wearable robots. The development of smart textiles embedded with robotic fibers can change shape, temperature, or color in response to environmental stimuli or user commands, pushing the boundaries of fashion and functionality. **[2]** The union of wearable robotics and fashion is an exciting field that combines engineering and creative design. By optimizing structural components it is possible to create garments that are not only visually appealing but also enhance the wearer's experience.

Past/related work

Various techniques have been used to improve the design and functionality of assistive devices. A significant approach involved *musculoskeletal load analysis* **[3]**, which examines how wearable robots impact the human body's muscle load during tasks. The goal is to optimize the design and control of wearable robots to reduce the load on targeted muscles. However, a common challenge is that the use of wearable robots can lead to increased load on non targeted muscles which results in minimal net improvement.

Another technique used is *simulation-based design* **[4]**, using dynamic optimization to predict the performance of wearable robots under various conditions. This allows for virtual prototyping, reducing the need for costly physical testing. Despite its advantages, simulation-based design faces challenges in accurately modeling human-robot interactions and validating simulations against experimental data. The complexity of human biomechanics and the individual characteristics of each user, make it difficult to achieve precise simulations.

Topology optimization **[5]** has also been applied to wearable robotics to create structures that are light and stiff; this approach involves optimizing the material distribution to achieve the desired performance. Due to the unpredictability of users, developing control systems that can adapt to the wide range of human movements and varying user needs is very complicated.

Despite these advancements, current methods in wearable robotics often face limitations related to computational complexity and validation accuracy, the intricate nature of human-robot interactions and the need for personalized designs require sophisticated modeling and control strategies; however, achieving high-fidelity simulations and real-world validation remains a challenge. The gap between theoretical models and practical applications highlights the need for continued research to refine these techniques and develop more effective and user-friendly wearable robotic systems.

Models/algorithms

Initial model setup

The goal is to design a wearable robotic system with beams connected to a mounted ring supporting the petals of the 'blooming flower' dress/mechanism. Each beam would rotate from 90 to 180 degrees by motors and would be affected by dynamic forces, such as walking or movement. The system needs to preserve structural integrity to prevent deflection and damage while minimizing weight. Weight is a significant factor for the wearer's comfort.

To calculate the deflection of a beam under a known force, a static model is created. This model involved calculating the moment of inertia of the beam's cross-section and using beam deflection formulas to predict how the beam would bend under the petal weight. The formula used for the deflection of the beam is:

$$\delta = \frac{FL^3}{3EI}$$

Where L is the length of the mean, E is the modulus of elasticity of the material, and I is the moment of inertia of the cross-section. It is relevant to note that this model only considered the static forces applied by the petal weight and did not include the dynamic forces created by the wearer's movement or the rotational motion of the beam as the motor turned.

Incorporating dynamic forces and rotation

After the initial static model, the next step was to incorporate dynamic forces that simulate real-world walking or motion. These dynamic forces were modeled using a sinusoidal function, as walking forces usually follow a periodic pattern. The total force applied to the beam was a combination of the static gravitational force (petal weight) and the dynamic sinusoidal force.

The dynamic force was given by:

$$F_{dynamic} = A * sin(\omega t)$$

Where A is the amplitude of the dynamic force, ω is the angular frequency of the sinusoidal force, and t is the time.

The challenge was in accounting for how the beam deflects as it rotates. As the beam rotates from 90° to 180°, the effective force (the combination of static and dynamic forces) changes, which affects the deflection. Also, as the rotation progresses, the torque on the motor increases.

The rotation angle (θ) of the beam, was introduced as a variable in the deflection model. The effective force was calculated as:

$$F_{effective} = -F_{static} * cos(\theta) + F_{dynamic}$$

Where θ is the rotation angle of the beam, ranging from 90° to 180°. The complexity of combining rotational motion with dynamic loading led to challenges in both modeling the forces and ensuring the optimization process was feasible.

The optimization model integrated weight calculations as part of the objective function, balancing the trade-offs between structural performance and lightweight design.

$$Weight = Volume\ x\ Density\ x\ g$$

$Volume = L\ x\ h\ x\ \omega_{beam}$, where L is the length of the beam, h is the height and ω_{beam} is the width.

Modeling challenges

One of the major difficulties was modeling how the dynamic forces impacted the beam as it rotated. The combination of a sinusoidal dynamic force and the rotation introduced nonlinearities in the deflection formula. To deal with the dynamic forces and weight constraints, *auxiliary variables* were introduced in the CVX model. These auxiliary variables made the optimization process easier to manage. Variables like T_1 and T_3 were introduced. These represented the force and deflection constraints. T_1 was used to represent the product of force and the length of the beam, while T_3 was used to represent the material properties and moment of inertia. These variables helped in separating the linear and nonlinear parts of the model, making it easier to solve.

Since the model had to choose between two materials, PLA and PETG, *binary decision variables* were used to represent the material choice.

The most challenging part was modeling the dynamic forces. Initially, *second-order cone programming (SOCP)* to solve the problem was considered as SOCP is useful for convex problems that involve quadratic constraints, but due to the nonlinear nature of the dynamic forces and the beam's rotational motion, the SOCP approach failed to converge to a feasible solution.

The problem became solvable when using CVX with auxiliary functions. CVX allowed for convex approximations of nonlinear constraints and could handle the binary material selection, linearized deflection constraints, and moment of inertia constraints.

Results

The final output showed that **PLA** was the optimal material for the beam, with a beam length of **23.2932 cm** and a height of **0.4714 cm**. The computational time required to reach the solution was 0.28 seconds. These results were achieved by considering the static, dynamic forces and the rotational motion of the beam. The optimized parameters ensured that the beam remained within the deflection limits and stayed below the max torque threshold for the motos used.

The deflection over rotation angle, as seen in **Figure 1**, shows how the deflection increases as the beam rotates from 90° to 180°, as expected due to the increasing moment. Comparing different materials, PLA provided a better solution in terms of deflection. As seen in **Figure 2**, PLA had a slightly lower deflection for the same set of parameters, making it the preferred material for this application.

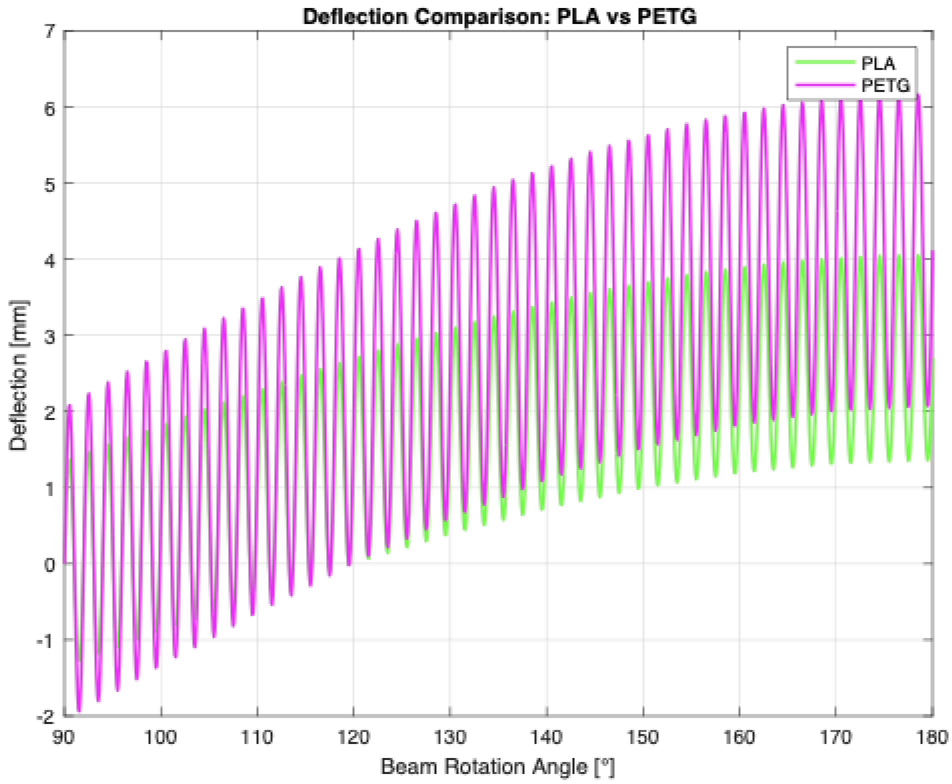

Figure 1: Deflection Comparison: PLA vs. PETG

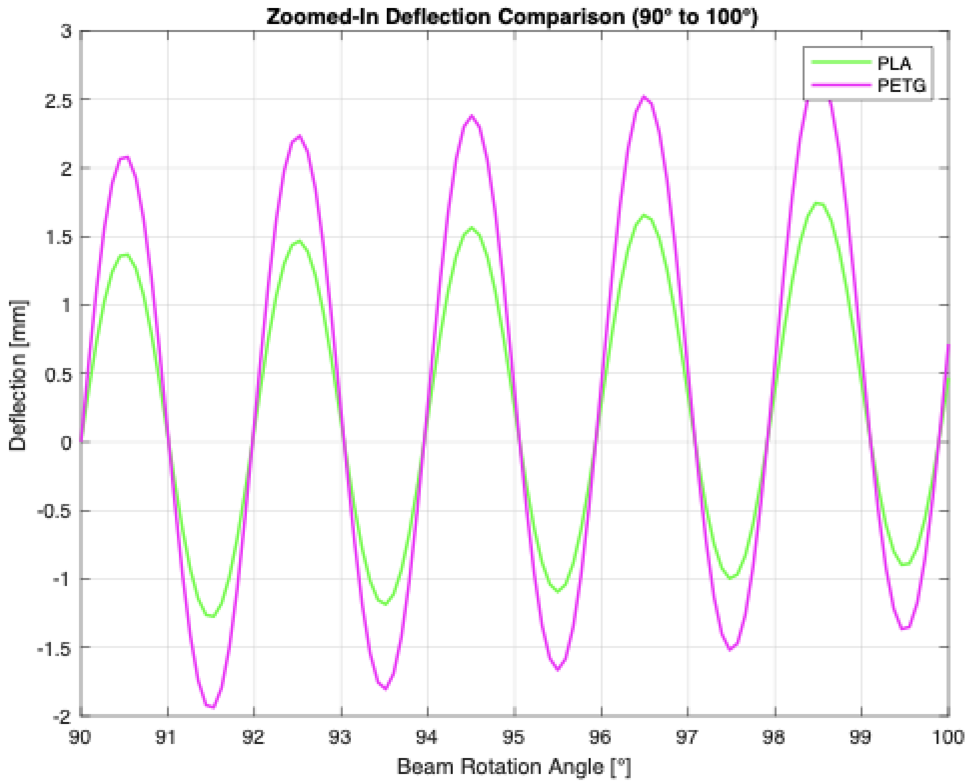

Figure 2: Zoomed-in Deflection Comparison: PLA vs. PETG

CVX combined with SDPT3, a semi definite programming (SDP) solver, provided a robust model. Despite the complex nonlinear constraints, this method was able to handle the problem once the auxiliary functions and linear approximations were used. This was a major improvement over the initial attempts with SOCP, which did not work with high-order nonlinearity. The system could handle the optimization of both the material selection and beam geometry ensuring the selection and torque constraints. The use of binary variables for material selection simplified the process. The running time of the process was manageable, as it only required 23 iterations to converge.

```
Calling SDPT3 4.0: 30 variables, 11 equality constraints
  For improved efficiency, SDPT3 is solving the dual problem.
------------------------------------------------------------

 num. of constraints = 11
 dim. of sdp    var  =  4,   num. of sdp  blk  =  2
 dim. of linear var  = 24
*******************************************************************
  SDPT3: Infeasible path-following algorithms
*******************************************************************
 version  predcorr  gam  expon  scale_data
  HKM      1      0.000   1        0
```

```
it pstep dstep pinfeas dinfeas  gap      prim-obj      dual-obj    cputime
-------------------------------------------------------------------
 0|0.000|0.000|4.1e+00|6.7e+00|1.0e+12| 4.325646e+10  0.000000e+00| 0:0:00| chol  2  1
 1|0.000|0.000|4.1e+00|6.7e+00|1.0e+12| 4.325400e+10  3.112684e+05| 0:0:00| chol  2  2
 2|0.000|0.000|4.1e+00|6.7e+00|1.0e+12| 4.325467e+10  8.986270e+05| 0:0:00| chol  2  2
 3|0.000|0.002|4.1e+00|6.7e+00|1.0e+12| 4.325408e+10  4.460393e+06| 0:0:00| chol  2  2
 4|0.034|0.001|3.9e+00|6.7e+00|1.0e+12| 4.361185e+10  6.770810e+06| 0:0:00| chol  2  2
 5|0.004|0.191|3.9e+00|5.4e+00|8.8e+11| 4.360876e+10  3.461332e+08| 0:0:00| chol  2  2
 6|0.447|0.232|2.2e+00|4.2e+00|7.8e+11| 4.321024e+10  6.296511e+08| 0:0:00| chol  2  2
 7|0.601|0.770|8.7e-01|9.6e-01|2.4e+11| 3.765535e+10  7.275475e+08| 0:0:00| chol  2  2
 8|1.000|0.870|6.3e-08|1.2e-01|3.6e+10| 8.026533e+09  1.271559e+08| 0:0:00| chol  2  2
 9|0.927|0.972|5.3e-09|3.5e-03|1.3e+09| 5.869371e+08  2.454497e+06| 0:0:00| chol  1  1
10|0.638|0.703|2.3e-09|1.0e-03|5.7e+08| 2.555112e+08 -8.759556e+04| 0:0:00| chol  1  1
11|0.862|0.759|3.1e-10|2.5e-04|1.8e+08| 6.109848e+07  1.456460e+04| 0:0:00| chol  1  1
12|0.941|0.829|1.8e-11|4.3e-05|3.6e+07| 1.022942e+07 -1.037521e+03| 0:0:00| chol  1  1
13|1.000|0.933|2.2e-13|2.9e-06|3.0e+06| 1.121610e+06  4.613925e+01| 0:0:00| chol  1  1
14|0.969|0.906|1.4e-14|2.7e-07|3.2e+05| 1.650629e+05  3.155449e+00| 0:0:00| chol  1  1
15|1.000|0.956|2.1e-14|1.2e-08|5.5e+04| 4.771922e+04 -1.258409e+00| 0:0:00| chol  1  1
16|0.978|0.990|7.6e-15|1.7e-10|2.3e+03| 2.267630e+03 -1.684719e-01| 0:0:00| chol  1  1
17|0.981|1.000|7.0e-16|3.0e-11|4.7e+01| 4.456025e+01 -1.638738e-01| 0:0:00| chol  1  1
18|0.975|1.000|6.4e-16|1.5e-11|1.5e+00| 1.242506e+00 -1.366873e-01| 0:0:00| chol  1  1
19|0.997|0.970|4.2e-16|8.3e-12|6.8e-02| 5.407099e-02  4.277249e-02| 0:0:00| chol  1  1
20|0.980|0.985|6.2e-16|8.5e-13|1.6e-03| 1.219073e-03  5.404402e-03| 0:0:00| chol  1  1
21|0.988|0.988|5.9e-16|8.1e-14|2.1e-05| 1.489127e-05  5.442516e-04| 0:0:00| chol  1  1
22|0.996|0.992|2.0e-14|6.8e-16|4.1e-07| 3.011560e-07  4.499887e-06| 0:0:00| chol  1  1
23|1.000|0.992|1.9e-15|4.1e-17|5.8e-09| 4.088847e-09  3.642166e-08| 0:0:00|
  stop: max(relative gap, infeasibilities) < 1.49e-08
-------------------------------------------------------------------
 number of iterations   = 23
 primal objective value =  4.08884746e-09
 dual   objective value =  3.64216555e-08
 gap := trace(XZ)       = 5.81e-09
 relative gap           = 5.81e-09
 actual relative gap    = -3.23e-08
 rel. primal infeas (scaled problem)   = 1.86e-15
 rel. dual     "        "       "      = 4.15e-17
 rel. primal infeas (unscaled problem) = 0.00e+00
 rel. dual     "        "       "      = 0.00e+00
 norm(X), norm(y), norm(Z) = 1.8e+04, 5.2e-01, 1.0e+06
 norm(A), norm(b), norm(C) = 2.0e+06, 1.8e+04, 1.4e+06
 Total CPU time (secs)  = 0.28
 CPU time per iteration = 0.01
 termination code       =  0
 DIMACS: 2.5e-15  0.0e+00  5.9e-17  0.0e+00  -3.2e-08  5.8e-09
```

Status: Solved
Optimal value (cvx_optval): -3.64217e-08

Optimized Beam Parameters:
L = 23.2932 cm
h = 0.4714 cm
Material = PLA

As seen in **Figure 3,** a prototype for this project was made before performing the optimization. The initial design, purely based on intuition, was created to test the system's functionality and validate the core concepts early in the development. After completing the optimization process, the results showed a significant disparity with the intuitive design. For the length of the beam, the prototype was **29.8 cm** while the optimized length showed to be **23.3 cm**. The prototype's thickness was **0.3 cm**, while the optimized thickness is about **0.5 cm**.

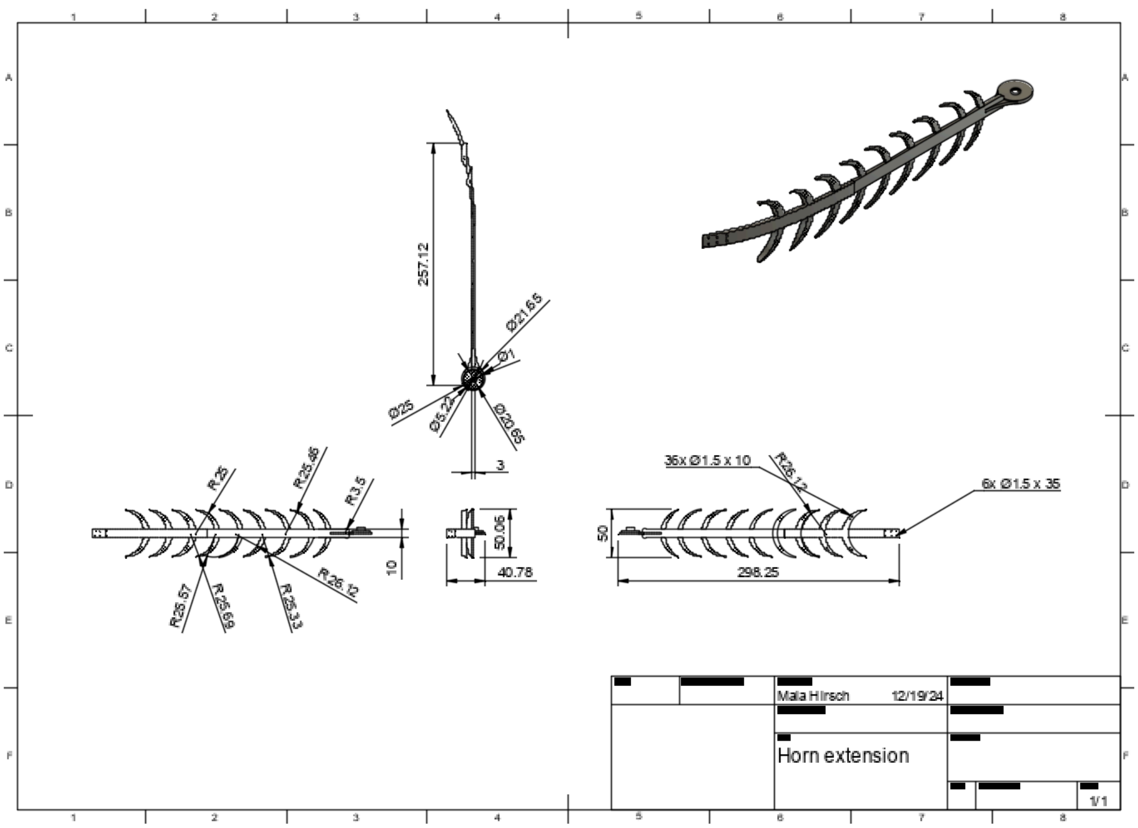

Figure 3: technical drawings of prototype beam

Conclusions:

The optimization approach that combined convex optimization with CVX and SDPT3, provided a way to balance competing design goals. The competing goals were between decreasing deflection, which tends to increase thickness and therefore adding material, and minimizing weight, which would try to reduce the amount of material.

One of the key lessons learned was the importance of nonlinear constraints in the problem, specially in the way forces interact. Modeling the dynamic loading forces and incorporating them into the optimization process was a significant challenge. Also, a lot of time was allocated at finding competing goals to optimize on. Previous attempts resulted in the minimum or lower value of a given parameter for this reason. Another important observation was the critical role of material selection in the system's performance. PLA, providing the lowest deflection and torque, suggests that material properties should always be considered in design problems where mechanical load and deformation are present.

Several areas for further exploration remain. One of these areas could be real-time adaptation of the system to changing dynamic forces, like the ones experienced during different stages of walking or other physical movements. This optimization focused on static beam geometry, but real-time adjustments for varying forces could provide a more responsive and adaptable system, improving the user comfort and the device design. Material innovations that could allow for better dynamic response or lighter, more flexible beams could also be explored to enhance the design. Given more time, refinement of the prototype would be prioritized, particularly adjusting the beam thickness and length, as well as exploring alternative materials. This would help bridge the gap between theoretical results and the practical requirements of the system.

References

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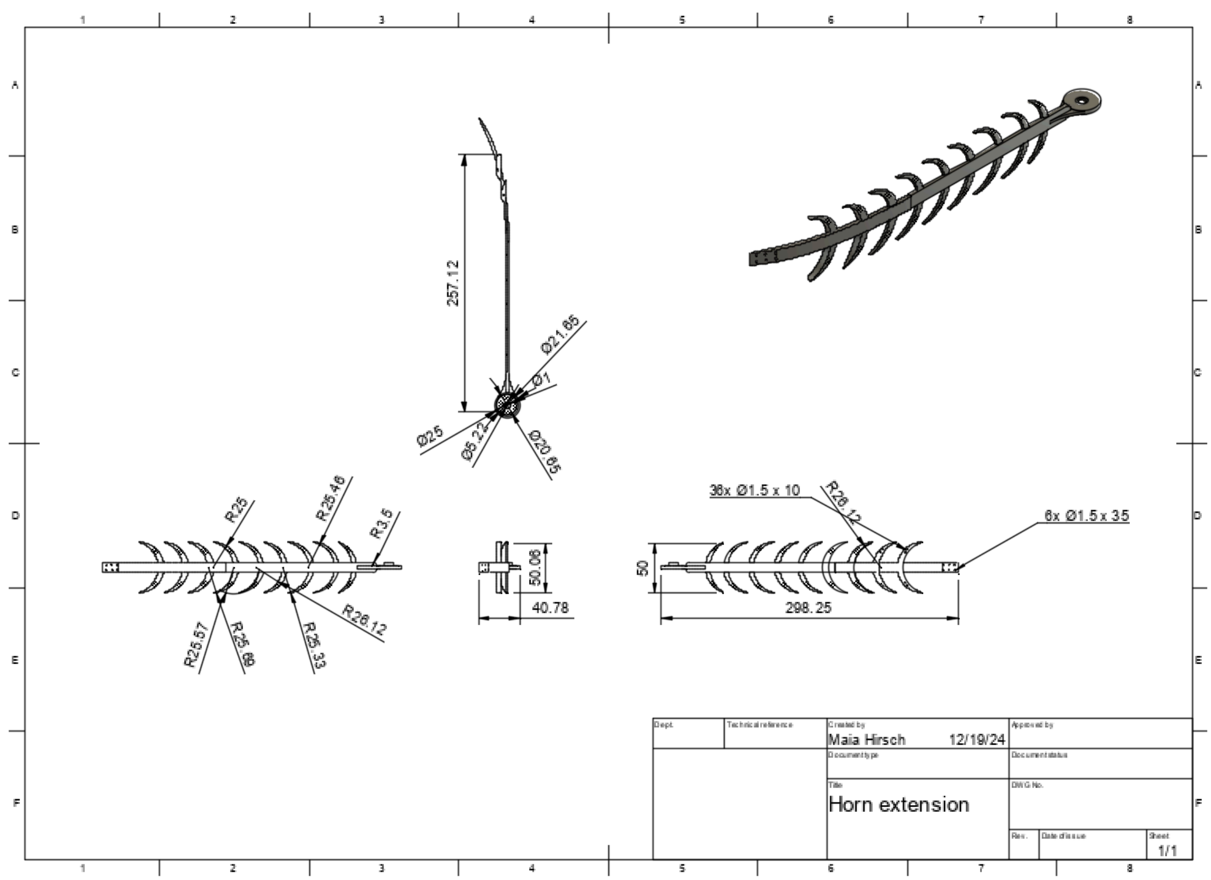
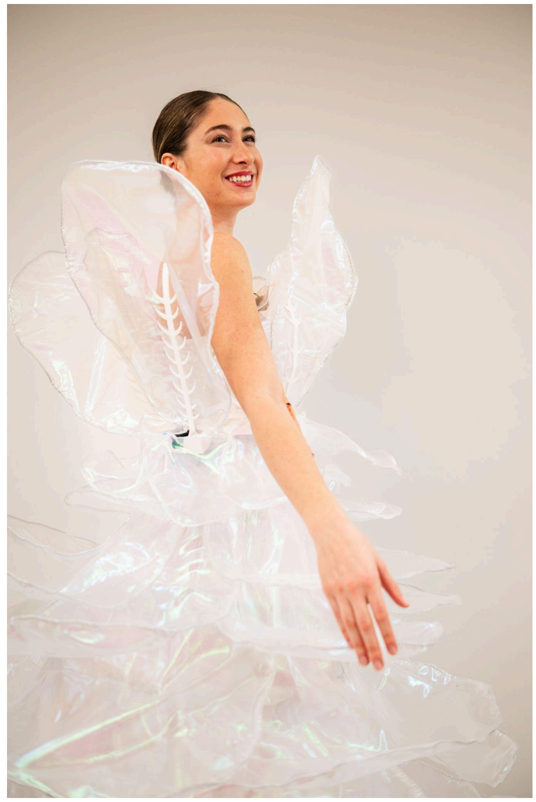
[5] Lanotte, Francesco, et al. "Adaptive control method for dynamic synchronization of wearable robotic assistance to discrete movements: Validation for use case of lifting tasks." *IEEE Transactions on Robotics* 37.6 (2021): 2193-2209.

Appendix
CAD/Drawings



Photos and videos

See the working blooming mechanism [here](). For integration with capacitive touch sensor [here]()