

Computational and Experimental Design Exploration of 3D-Printed Soft Pneumatic Actuators

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Soft robotics are known for their unique advantages over conventional rigid robotics, which include safer human–machine interaction, delicate handling of fragile items, and greater durability. Soft robotic actuators are essential components in soft robots as they produce the organic motions that rigid robotic actuators have difficulty in mimicking. Pneumatic actuators (PAs) are a type of soft robotic actuator that utilizes pneumatic pressure for actuation and are commonly used; however, the relationship between their design and actuation performance is not well understood. Herein, a cubic kernelized support vector regression (SVR) model based on finite element analysis is used to explore the design space of bending PAs with respect to their bending angles through the investigation of the dependencies between different design parameters. The model obtained from the SVR is then tested by experimentally comparing the bending angle of different 3D-printed PAs from within the design space. The bending torque, an indicator of the actuation force of the PA, is also measured and compared for different design configurations. This study provides a computational and experimental framework and paves the way for future work on PAs, which has the potential to greatly propel the advancement of soft robotics.

Soft robotics is a growing field of interest for the application of robotics in environments where humans and robots are expected to interact in a tactile manner. For example, soft robotics may significantly enhance safety in human–robot interactions sensitive medical procedures, more reliable automated handling of fragile items in production lines, or better maneuverability in rough terrain.^[1] Force limits and artificial compliance can be programmed into rigid robots; however, soft robots offer inherently better mimicry of features found in biological systems. An important part of the development of soft robotics is the study of soft actuators. Work has been reported on different types of soft actuators based on different actuation mechanisms including fluid-driven (hydraulic and pneumatic),^[1d,2] tendon-driven,^[3]

and electroactive polymer-driven actuators.^[4] Pneumatic actuators (PAs) work through the pressurization of compliant chambers to achieve motion. Different types of PAs are used to achieve different motions including bending, contracting, extending, and twisting.^[2e] PAs are inexpensive, easy to fabricate and operate, and can effectively mimic organic motions while also being able to output relatively large actuation forces.

There are three major techniques used to fabricate PAs: molding, lithography, and 3D printing.^[1e,2a,5] The scale, design, and performance of PAs are heavily dependent on the capabilities and limitations of the fabrication technique used. The fabrication technique dictates the material used to fabricate the PA which is critical as the mechanical properties of the material greatly affect the performance of the joint. The 3D printers can fabricate parts with complex geometries, otherwise impossible to build with traditional methods.^[2b,6] This

is useful in the fabrication of soft robots, which are generally inspired by complex biological systems in nature. The potential ability to seamlessly integrate actuators into a robotic system without having to assemble structural elements with them is an inspiring advantage of using 3D printing in this context. PAs can be fabricated using different 3D printing technologies including fused deposition modeling (FDM), stereolithography, and selective laser sintering (SLS). FDM has been widely adopted by prototyping departments, hobbyists, and researchers due to its overall low cost, wide material selection, and ease of use.^[5,7]

Due to their complex designs and extreme compliance, the actuation mechanisms of PAs are not well understood. There is a lack of understanding in the literature regarding the influence of PA design parameters on key performance characteristics such as actuation range, power output, and endurance.^[2e] Due to the vastness of the design space of a PA, using experiments to perform design studies would require an inordinate amount of time. It is far more feasible to perform a design exploration of the PA using finite element simulations that have been validated through the comparison of a few designs. In recent years, researchers have applied various methods to design PAs including topology optimization of the pneumatic channel shell,^[8] geometric optimization of bellow-type PAs,^[9] and channel optimization of cylindrical PAs.^[10] In this work, we focus on bellow-type designs. In addition to the wall thickness and bellow width parameters that have been studied in previous works,

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we perform a design exploration over a wider design space which includes bellow height, depth, and thickness. Moreover, we investigate the tradeoff between two critical performance characteristics of PAs, actuation range and torque output. Machine learning techniques,^[11] taking as inputs, data collected from FEA simulations are used to make predictions, which further extend the reach of this design exploration. The knowledge gained from this exploration is important for understanding the actuation mechanism of PAs which will aid in their development and will allow for them to be confidently and reliably used in more applications.

In this article, we report a study on the bending angle of a 3D-printed bending PA (Figure 1a) in relation to its design using finite element analysis (FEA) and experiments. The bending angle of a PA is critical as it defines the range of motion of the actuator. Herein, FEA is utilized to explore the design space of the bending PA with respect to its bending angle. Furthermore, bending torque output is experimentally investigated to understand the tradeoffs between choosing a PA with optimal bending angle design parameters versus optimal bending torque design parameters. From here on out, “PA” will refer to “bending PA.” Depending on the base design of the PA, there may be several design parameters to be investigated in terms of how they affect the bending angle. In this work, three design parameters are considered as defined in the CAD drawing in Figure 1b, the bellow width, w_b , height, h , and thickness, d . The selection of these specific parameters is based on several

factors including initial simulations. From our simulations, it is observed that bellow height and width present an interdependent relationship influencing the bending angle; therefore, these parameters are the focus of this work. The advantage of our method is the feasibility of creating a 3D contour plot consisting of only parameters that demonstrate a dependency in influencing the bending angle. The FEA results from the exploration of the bellow height and width are used to generate a model that describes the design space using support vector regression (SVR) from which a convenient contour plot of the design space is generated. The SVR is essentially providing a smooth and accurate interpolation of the data over the design space. SVR compared with other machine learning algorithms offer the best combination of accuracy and generality for our problem and more discussion is highlighted in the Experimental Section. In addition, the bellow depth is briefly investigated for its effect on the bending angle.

A PA takes advantage of its anisotropic compliance to bend under pressurization. In a monolithic PA, this anisotropic compliance stems from its geometry that contains localized stiff and compliant regions. A common design that results in bending under pressure is the bellowed actuator design.^[2e,g] The design parameters in this study are the bellow height (h), width (w_b), and thickness (d) (circled in Figure 1b), where h is the length from the tip of the bellows to the inside surface of the flat side, w_b is the width of each bellow, and d is the thickness or depth of the bellow. Figure 1c shows two different design instances,

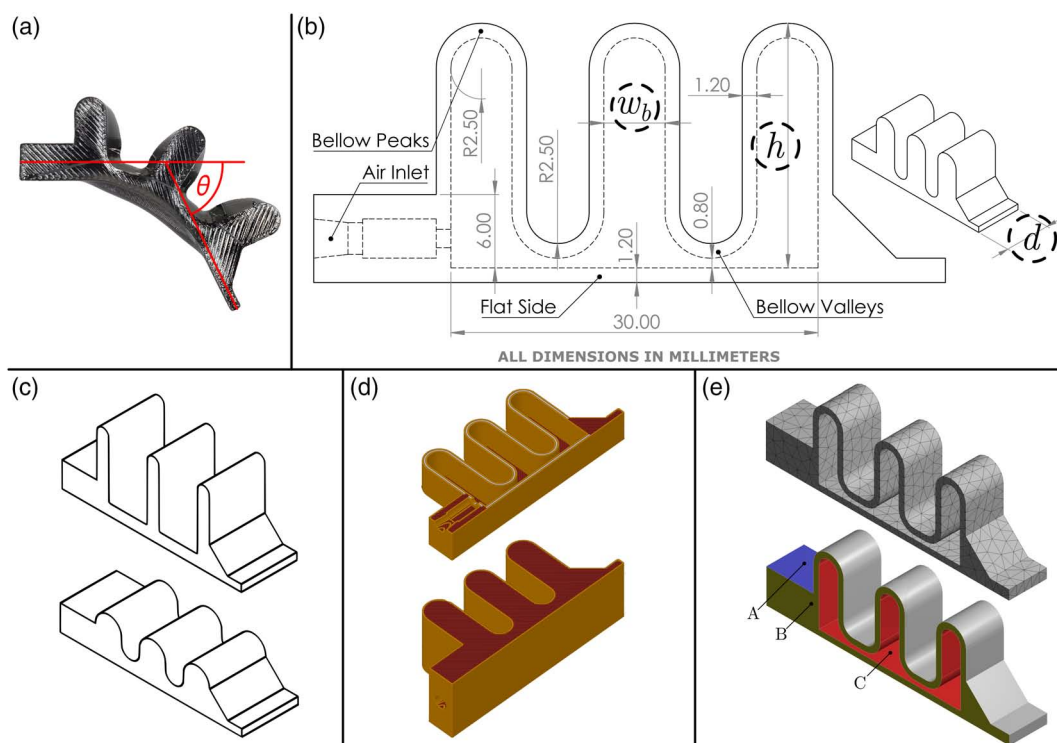


Figure 1. a) Definition of the bending angle response. b) Engineering drawing of the PA with critical geometrical features. Dimensions w_b , h , and d are taken as parameters for the study. All other dimensions are kept constant. c) Depiction of the PA with different parameters within the design space of the investigation. The upper actuator has long and thin bellows, whereas the lower actuator has short and wide bellows. d) Sliced PA shows lack of support material inside the bellows. e) Mesh and boundary conditions of the PA. The PA is fixed from region A (blue in figure), a symmetry boundary condition is applied to face B (tan), and 0.15 MPa is applied to the inside faces of section C (red).

corresponding to two points in design space, to clarify how different combinations of the height and width affect the PA geometry.

The objective of this study is to understand the design space of a 3D-printed PA. The design of the PA is heavily influenced by the capabilities and limitations of FDM 3D printing. One critical, unique property of FDM 3D printing is its ability in printing overhanging or suspended structures. Without this ability, the internal support structures would be irremovable due to the PA being monolithic, which restricts access to internal features. This allows for the design of the “top” and “bottom” faces (called this way due to the print orientation of the PA as shown in Figure 1d) to be flat. The top face of the PA covers the bellow chambers and is the last feature that is 3D printed. To avoid support material inside the bellow chambers, the top face is 3D printed using a common bridging technique that allows for printing in mid-air. The bridging technique bridges the gaps between edges that are of the same height; therefore, the top face is designed to be flat. Inconveniently, the flatness of the top and bottom faces hinders the compliance of the PA significantly. Therefore, the surface area of the flat faces at the valleys of the bellows, where most of the strain takes place, is minimized by reducing the distance between the valley of the bellows to 0.8 mm, as shown in Figure 1b.

To reduce the complexity of the design space, preliminary simulations and experiments were performed, which allowed for the elimination of design parameters that fell into the following three categories: 1) the parameter has a predictable effect on the bending angle (e.g., the length of the bellow chamber and number of bellows); 2) the parameter is already optimal (e.g., the thickness of all walls and distance between valleys and flat side); or 3) the parameter does not affect the bending angle and so is kept at a reasonable length (e.g., all other dimensions). For example, the thinner the walls of the bellows, the greater the bending angle; thinner walls increase the compliance of the joint. However, the walls have been set to a thickness of 1.2 mm due to the tradeoff between airtightness and compliance.

FEA is used to compute the bending angle of the PA with different design parameters (Figure 1e). An experimental approach would require the printing of hundreds of PAs which would be expensive and time costly. Thus, the design space is explored using static finite element simulations. There are numerous machine learning techniques that can be used on the FEA data. However, taking advantage of the low dimensionality of the data (bending angle prediction given two of its design parameters), a preliminary visualization is performed which shows the existence of a smooth curved surface where all the data rest on; therefore, other more advanced models are left out for simplicity. A fivefold cross-validation is performed on the data points to compare the loss of various linear and SVR models with different hyperparameters. The finalized model is determined to be cubic kernelized SVR and its response over the whole design space is shown in a contour plot in Figure 2a and it fits the data with an R^2 value of 0.98 (see details of the model in the Experimental Section). The model response versus the simulation response is shown in Figure 2b, demonstrating the goodness of fit.

As shown in Figure 2a, the bellow width has a significant influence on the bending angle of the PA; reduced bellow widths result in relatively larger bending angles within the design space.

For instance, the model reveals a 13% increase in the bending angle while changing the bellow width from 4 mm to 2 mm along the steepest gradient of the model with respect to the bellow width, where the bellow height is constant at 20 mm. Moreover, pushing the design parameters further from the optimal width speeds up the drop of bending angle (the largest magnitude of the negative gradient at the margin of the bellow width dimension). This gradient distribution can be verified intuitively through extreme cases. At large bellow width, one would expect a large bending angle drop especially at the point where all bellows merge into one continuum which hinges the flexibility between bellows. At small bellow width, one would expect a similar result at the point where all bellows become solid which hinges the flexibility of bellow themselves (bellows are supposed to swell). Taking into consideration the aforementioned two extreme cases plus the continuity of the design space, the SVR model matches the physical intuition quite well. These results point to the significance of the valleys of the bellows in terms of increasing the bending angle of the PA.

Furthermore, based on the simulations, the change in thickness of the bellows seems to have a predictable effect on the bending angle performance. The bending angle increases with increasing bellow thickness; however, this increase varies across the bellow width and height design space. To capture this variance, simulations are performed with PAs at 12 mm and 6 mm thickness with varying bellow widths and height and the ratio $\theta_{2d}/\theta_d = 6 \text{ mm}$ is obtained and shown in Figure 3. In the figure, θ_{2d} and θ_d are the bending angle of the 12 mm and 6 mm bellows, respectively. It can be shown that an increase in over 200% can be seen across the design space with slight variances. More work is needed to fully explore how this trend behaves at larger and smaller thicknesses; however, these results are sufficient to show that the dependency between the bellow thickness and the other parameters are not as significant as the dependency between the bellow height and width.

The strain fields obtained from the FEA, shown in Figure 2c, show large strains at the valleys of the bellows which suggest the importance of the valleys as well. Since thinner bellows result in more compliant valleys, the bellow width trend in the Figure 2a suggests that the valleys serve as primary hinges with which the entire structure bends. Furthermore, the model shows that along its steepest gradient with respect to the height where the bellow width is kept at 2 mm, the change in bellow height required to achieve the same 13% increase, as mentioned previously, is 10 mm. Therefore, the bellow height affects the bending angle less significantly than the bellow width. It is of note that the SVR model points to an optimum dimension for both the bellow height and width; however, this can be purely attributed to the nature of the model which will not necessarily translate to FEA or experimental results. The primary takeaway from the model is the trends in the effects of the alteration of the dimensions with the design space of this study.

To experimentally validate the trends of the SVR model, three design points, shown in Figure 2a, from the design space were 3D-printed and compared with the model and simulations. These three design points were selected to represent different bending angle performances within the domain. Results show that there is good agreement in the bending angles of the 3D-printed (θ_{exp}), SVR model (θ_{mod}) and FEA (θ_{sim}) design points 1 and 2, as shown

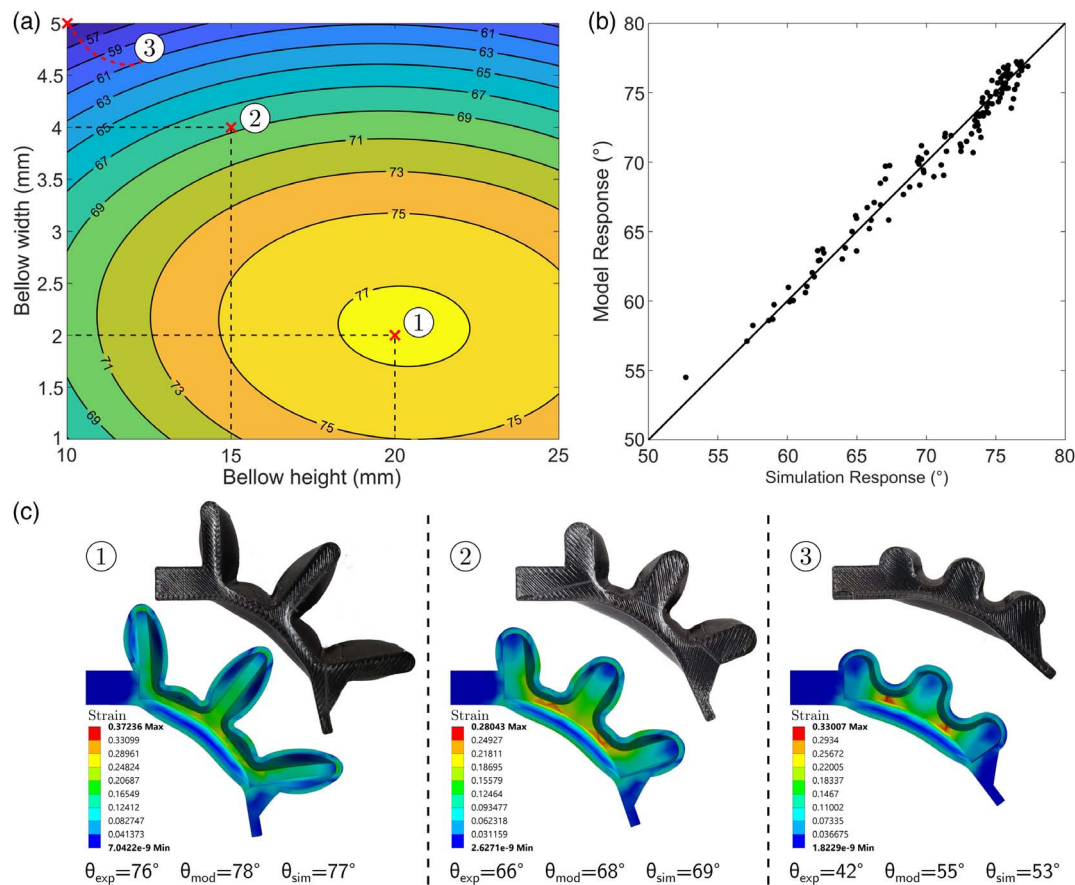


Figure 2. a) Contour plot of bending angles from model response surface. Three design points are chosen for experimental testing (as shown in the figure). b) Model versus simulation response for all data points shows excellent agreement. c) Experimental results and simulation strain field plots for all three design points. Bending angle obtained from experiments (θ_{exp}), model (θ_{mod}), and simulations (θ_{sim}) are reported.

in Figure 2c. We would like to make a note that the third experimental result from the simulation and model predictions exhibits a discrepancy due to certain regions in the PA approaching strains exceeding the domain of approximated linear response. Design point 3, further, is closer to the fringe of the model training set as shown in Figure 2a, and so might be beyond the scope of the model. Nevertheless, the model still predicts the correct trend in the direction of design point 3. In the FEA setup, the PAs are only pressurized up to 0.15 MPa. Therefore, to confirm the consistency of the results of the SVR model with different pressures, the bending angles of the three design points shown in Figure 2 are experimentally measured at different pressures of up to 0.4 MPa. The results from these measurements are shown in Figure 4a and the results are indeed consistent as the order of superiority of the PAs remains unchanged over the pressure range. The response of the PAs is clearly nonlinear with respect to the applied pressure. The PAs can withstand a maximum pressure of 0.6 MPa before explosively failing; therefore, the pressures for all experiments were limited to 0.4 MPa. This can potentially be improved by tuning the 3D-printing parameters to promote greater adhesion between layers.

The performance of the PA is also evaluated in terms of its static bending torque output. This is an important property as

it determines the ability of the PA to perform its intended operation, providing the force needed to sufficiently actuate under varying loads. Interestingly, the plot in Figure 4b shows that design 2 outperforms all other designs with regards to torque output. The difference in the torques between the designs across the pressures appears to steadily change within the range investigated, with almost no difference at a pressure of 0.1 MPa and a difference of 0.03 Nm between designs 2 and 3 at a pressure of 0.4 MPa. This means that bending angle performance does not necessarily indicate bending torque performance. The torque output seems to be fairly linear with respect to the pressure applied to the PA. These results set the foundation for more work toward fully understanding the tradeoffs between optimizing both the actuation range and torque output.

In summary, a 3D-printed bending PA, which can be customized and fabricated through additive manufacturing, was studied using a cubic kernelized SVR model based on FEA data to understand how its design affects its bending angle and to make predictions on the response of different design parameter values. Two independent design parameters were identified in preliminary investigations: the bellow height and bellow width. The SVR model showed that thinner bellows increase bending, bellow height has an optimal value of 20 mm for the scale at which

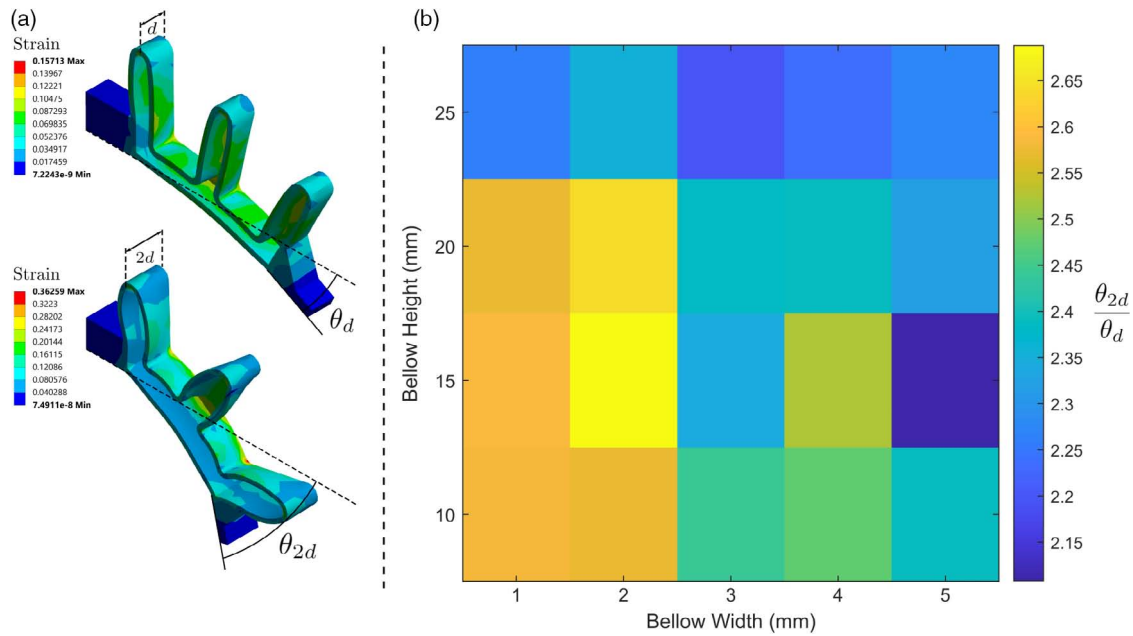


Figure 3. a) Bending angle simulations for two PAs with bellow widths and heights from design point 2 with different thicknesses. Top PA has half the thickness of the bottom PA. b) Plot of the bending angle increase factors for 20 design points. Each cell represents the ratio between the bending angle of a PA design with a thickness (d) of 12 mm (θ_{2d}) to one with a thickness of 6 mm (θ_d).

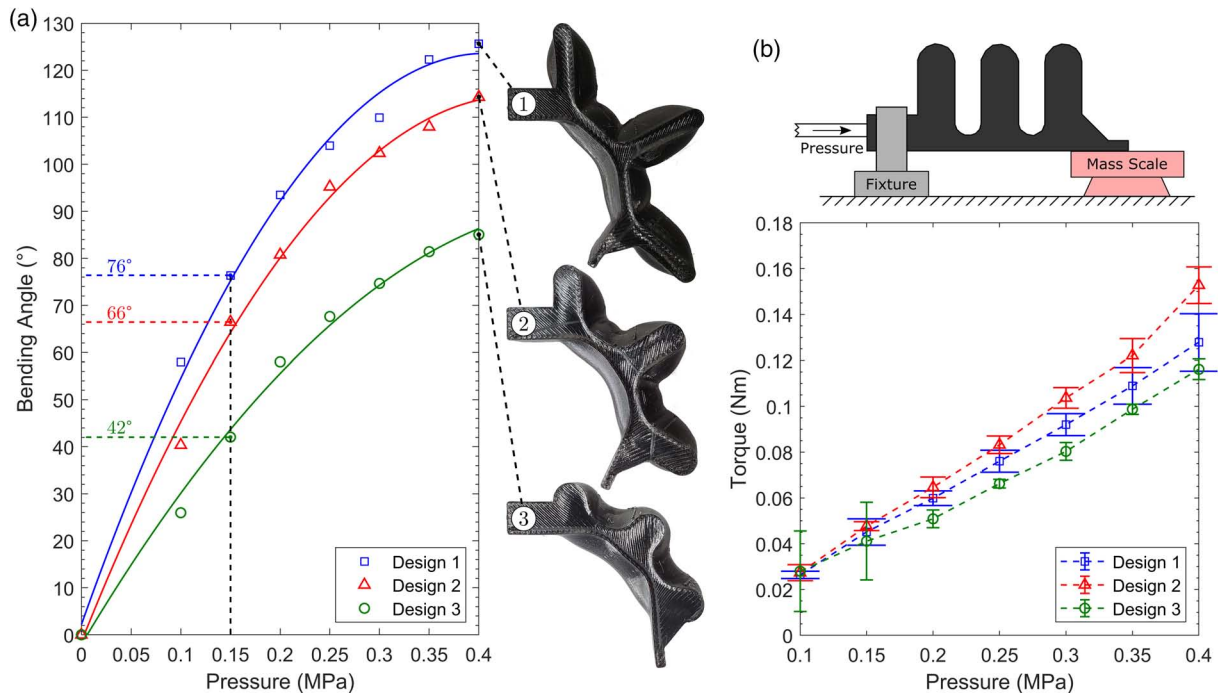


Figure 4. a) Experimental measurements of PA bending angles for the three designs at different pressure levels. Solid line is a polynomial fit to the measured points. The relative superiority of the designs is consistent at different pressure levels. Bending angles at 0.15 MPa are used for comparison with simulations. The different designs pressurized at 0.4 MPa are shown on the right side of the plot. b) Torque output measured from experiments for the three designs. Schematic of experimental setup is shown in top portion of the plot.

the PAs were designed in this work. Three design points from within the design space of the SVR model were 3D-printed and were measured for their bending angles to compare and validate

the model. Experiments had good agreement with the model in terms of variational trends. Furthermore, the bending torque of the three design points was experimentally evaluated and plotted

for different pressure levels. The plots showed that superior bending angle performance does not necessitate superior bending torque. Future work could include a similar framework to that of this article in which simulations and experiments are used to investigate not only the actuation range, but also the torque output of the PA in different conditions. This will allow for a better understanding of the PA design space and the objective trade-offs, which would result in more appropriate utilization of PAs for different applications.

The 3D-printed PAs have the potential to revolutionize the way soft robots are designed and fabricated. This study lays the groundwork for their further development and understanding. Although soft robotics currently mainly operate in highly specific applications, a better understanding of 3D-printed PAs will allow for improved control over the actuator which in turn leads to the increased prevalence of soft robotics in many more applications.

Experimental Section

The finite element simulations were performed using ANSYS Mechanical APDL with large deformations. The material was set to have linear isotropic elasticity with a modulus of 15 MPa^[28] and Poisson's ratio of 0.49. Because our simulations had shown that the printing material exhibited a relatively linear response at low strain levels among the design points, within the domain of each PA, a linear elastic material model was used as a very close approximation (with the added benefit of decreased computational cost). The left end of the PA was fixed and a uniform pressure of 0.15 MPa was applied on all internal faces of the bellows. This specific pressure value was selected to avoid excessive strains and yet still achieved quantifiable and comparable bending angles. Figure 1e shows the simulation setup including the mesh and the boundary conditions applied to the model. The design parameters were varied within a design space bounded by limits set through the consideration of the applicability, functionality, and printability of the joint in the extremities of the design space. For example, an excessively long height dimension on the joint would lead to restrictions in applicability and bellow widths below 0.4 mm can lead to poor printing reliability due to deposited traces overlapping. A total of 117 simulations were run and then input into an SVR algorithm, using the Regression Learner package in MATLAB, to model the bending angle response. The PAs are 3D-printed using a Prusa i3 MK3 FDM 3D printer. The printing parameters for the NinjaFlex filament, used to 3D-print the joint, were shown in Table 1. NinjaFlex is a type of thermoplastic polyurethane (TPU) produced by NinjaTek (a brand of Fenner Drives) that is capable of large elastic strains and has a very low elastic modulus which makes it suitable for this application as more compliance results in larger bending angles. The elastic properties of the NinjaFlex material for use in the FEA were taken from the study by Yap et al.^[28]

Table 1. Printing settings for Prusa i3 MK3 FDM 3D printer used to print the EIA.

Printing setting	Setting value
Bed temperature	80 °C
Print speed	10 mm s ⁻¹
Layer height	0.2 mm
Nozzle diameter	0.4 mm
Trace overlap	25%
Infill (in solid regions)	100%
Retraction	Off
Nozzle temperature	240 °C

To choose a proper machine learning model, a preliminary observation was performed on the data points as mentioned in the main text. The smooth curved shape of the data points led to the choice of kernelized regression models. A fivefold cross-validation was performed on the data points which divided the data into five equal groups and validated each candidate model on all five data groups to decide the choice of model and the hyperparameters. The best performance was achieved by a cubic kernelized SVR model which minimized the slackness between cubically augmented data points and the analytical response surface. The SVR model had a kernel scale of 1.69, slack threshold of 0.011, and slack penalty of 0.113 which gave the smallest validation loss of 0.0138 radians. The model performance was further tested on experimental results which were discussed in the main text. The torque output of the PA was evaluated by the use of a mass scale. Each pressurized PA was held at a static bending angle while applying force onto the mass scale. Then, to calculate the torque output, the moment arm of the PA was taken about the fixture point shown in the schematic of the experimental setup in Figure 4b. Each data point in the plot was the average of eight measurements at a set pressure which consisted of two PAs each tested four times. Aside from experimental variation, frictional interactions between the tip of the PA and the mass scale plate contributed to the error bars shown in the plot in Figure 4b.

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Conflict of Interest

The authors declare no conflict of interest.

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computational analysis, finite element method, pneumatics, soft robotics, 3D printing

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