

## Flex sensors embedded in soft pneumatic actuators with data-driven bending angle prediction

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**Abstract:** In order to give sensory input that may be used to forecast their bending angle during actuation, resistive flex sensors have been placed at the strain limiting layer of soft pneumatic actuators in this article. To test the soft actuators under regulated working circumstances, capture the sensory input that resulted, and synchronise this with the actual bending angles determined using a built image processing programme, an experimental setup was created. In this study, two data-driven modelling approaches—regression analysis and neural networks—were applied and compared to see how well they could forecast the bending angle response of the tested soft actuators under various input pressures and testing orientations. As a first step toward controlling this class of soft bending actuators, this eliminates the need for intricate analytical modelling and material characterization in favour of data-driven empirical models. As compliant soft gripper fingers that can be used in applications requiring both a "soft touch" and more controllable object manipulation, the ultimate goal is to develop a more controllable version of this class of soft pneumatic actuators with embedded sensing capabilities.

**Keywords:** soft grippers, pneumatic actuators, neural networks, regression analysis, image processing.

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### 1. INTRODUCTION

Soft pneumatic actuators (SPAs) with internal fluidic channel patterns (commonly referred to as *PneuNets*) are made of highly stretchable elastomer materials, which deform upon the pressurisation of the internal channels to create a predefined motion (Ilievski et al., 2011). The response of this type of actuators is governed by its morphology, which is defined by the geometry of the internal fluidic channels and the properties of the materials used in fabrication. A flexible but inextensible strain limiting layer, in the form of a paper or fabric, can be added at the base of a typical soft pneumatic actuator to prevent it from elongating and instead generate a bending motion that is analogous to that of a human finger. Hence, this class of bending actuators is being adopted as compliant soft gripper fingers, which are able to passively conform to objects of complex geometries and adapt to dimensional variations and location uncertainty (Deimel and Brock, 2015, 2013). In addition, the soft nature of the elastomer materials used to create these soft gripper fingers, allows grasping of delicate objects safely without damaging their surface (Galloway et al., 2016).

On the other hand, the complex deformation exhibited by the non-linear elastomer materials, commonly used to create the SPA based fingers, makes them difficult to be accurately modelled and controlled (Lipson, 2014). Some examples of recent work addressing the modelling and characterisation of bending SPAs include; an experimental characterisation of

the geometry of bending and rotary SPAs (Sun et al., 2013), finite element analysis (FEA) of cylindrical SPAs for surgical applications (Elsayed et al., 2014), theoretical modelling of a

soft snake robot based on the bending SPAs (Luo et al., 2014), and finally a detailed analytical and finite element modelling of a single chamber fibre-reinforced bending SPA (Polygerinos et al., 2015). One of the main challenges associated with the analytical and FEA modelling approaches is the need for accurate material models and relevant material coefficients, which can accurately describe the nonlinear behaviour of the used hyperelastic materials. This becomes even more challenging when SPAs are made of combinations of different materials, or when integrated with external reinforcements or embedded components. Furthermore, the manual process commonly followed in fabricating SPAs, is subject to variations that could arise during the material preparation, fabricating the required moulds, and bonding the actuators parts together. This means that expecting a consistent behaviour would be quite difficult

to guarantee among different samples of SPAs produced separately, due to the uncontrollable sources of variations. Moreover, when modelling contacts with external objects for grasping applications using SPAs, the FEA and theoretical modelling approaches would typically require some knowledge about the geometry and nature of the target object, which may not always be available in advance. In fact, soft gripper fingers in general are desired for their ability to passively accommodate a range of different objects, without the need for defining their geometry and material properties in advance. Therefore, it would be interesting to investigate alternative modelling approaches that can be used for predicting and controlling the behaviour of soft gripper fingers based on the bending SPAs, without the need for deriving precise physical and material models, or prior knowledge about the target objects to be handled.

The approach demonstrated in this paper exploits common data-driven modelling techniques, to derive reliable empirical models for bending SPAs using simple sensory feedback, which implicitly includes variations arising due to the manual fabrication process and accounts for the effect of gravity on the bending response when operating at different orientations. This approach not only lifts the need for deriving precise physical and material models that could be difficult to achieve in some cases, but is also not limited to specific elastomer materials or designs of SPA. The primary requirement of this approach however, is to generate sufficient experimental data that describes the behaviour of the modelled SPA in different situations, so that the derived models can be further generalised to new untrained scenarios. Hence, equipping SPAs with reliable sensing capabilities becomes essential to generate the required sensory feedback.

### 2.1 Embedded Flexible Sensing

Despite the fact that the passive compliance of SPA based soft fingers have the benefit of adapting to sources of variations and uncertainties without the need for expensive sensing and complex control, it has the drawback of limiting their application to simple pick and place tasks that do not require controlled manipulation and feedback about the grasp quality. The absence of active sensing also means that the orientation of a grasped object with respect to the soft gripper would be unknown, since the grasp was achieved passively. Hence, accurate object positioning would be difficult to achieve, which is required in applications such as assembly tasks for example. Thus, equipping SPA based soft fingers with some level of sensing capabilities that do not hinder their desired softness and compliance, should enhance their functionality and widen the scope of their application to include more complex manipulation tasks.

The primary controllable input parameter that can be varied during the actuation of soft actuators is the pressure of the pneumatic supply, which in turn controls the input flow rate. The actual internal pressure developed inside the soft fingers varies during the actuation, because of their continuous deformation. Yet, this pressure response can be easily measured using common pressure sensors connected to the supply tubes. The main challenge in sensing is measuring the bending motion of SPAs as they curve towards their base, without actually altering this behaviour with the sensing element itself. Hence, a flexible sensor is required that can be embedded at the base layer of an SPA, where extension is restricted by the constraint layer, to provide a measurable change in a physical parameter that can be directly related to the witnessed bending motion. This leads to need for highly flexible sensors that can be easily embedded within the soft body of SPAs, without limiting their desired compliance or altering their bending mechanism. This is one of several applications motivating research over the past few years into developing new concepts for flexible and stretchable sensors, which can be integrated with soft bodies in general (Lu and Kim, 2014). The main soft sensing techniques that could be smoothly integrated with soft gripper finger specifically for measuring their bending angle can be classified into three main categories as follows:

(1) The first approach is adding carbon content in different forms to elastomer materials, to make them conductive and hence creating soft sensing elements. This type of conductive elastomer based sensors has been incorporated with a soft gripper design that is actuated using linear displacements, to differentiate between different sized grasped objects (Issa et al., 2013). The main challenge with this type of soft sensing is the difficulty in producing sensors with consistent electrical properties, since repeated deformation may affect the distribution of carbon particles within the elastomer material. Also, electrical connections are difficult and may cause fluctuations in the sensory readings during actuation.

(2) A popular soft sensing approach now is achieved by filling internal channels imprinted within an elastomer body with a conductive liquid metal (EGaIn), to measure different physical parameters depending on the geometry of the conductive channel pattern (Dickey et al., 2008). Previous work demonstrated the use of this sensing approach to measure parameters such as: Multi-axis forces (Vogt et al., 2013), strain (Park et al., 2012), curvature (Majidi et al., 2011), and pressure (Park et al., 2010). The concept was incorporated recently with soft gripper fingers based on SPAs to achieve position and force control (Morrow et al., 2015). However, the manual process of injecting the embedded channels with the conductive liquid metal is delicate and not easily repeatable, which would become a challenge when considering larger scale production. In addition, the conductive EGaIn material is quite expensive.

(3) An alternative soft sensing approach was recently demonstrated by (Homberg et al., 2015), in which commercial resistive flex sensors were embedded in SPA based gripper fingers for haptic identification. Readings from the embedded flex sensors were clustered so that a trained algorithm can identify grasped objects based on the combined readings from all soft fingers. Another recent attempt for embedding simple flex sensors within soft gripper fingers was presented by (She et al., 2015), where the feedback was used to control the shape of the soft fingers actuated using shape memory alloys. The main advantage of this approach compared to using conductive silicone rubber or conductive EGaIn channels, is the fact that it relies on simple and inexpensive commercially available sensors that can be easily wired and embedded within the strain limiting layer of SPAs.

The work presented here follows the third sensing approach for measuring the bending angle of a typical SPA based soft finger design. This achieved by correlating the readings from the embedded flex sensors in conjunction with the internal pressure readings from on-board pressure sensors, to the actual bending angle measured using a developed vision system. This combination of multi-sensory feedback allows reasonable estimations of the bending angle of soft fingers, without the need for deriving accurate physical and material models. The aim is to ultimately utilise these inexpensive bending SPAs with embedded sensors, to act as more controllable soft gripper fingers that can be achieve accurate positioning in complex manipulation tasks.

The paper will proceed by briefly introducing a common fabrication process that can be followed to create soft gripper fingers based on the bending SPA morphology. Afterwards, in section 3 the platform involving the use of pneumatic control board and a high speed imaging system is presented, explaining how the soft fingers are actuated under different operating conditions to collect the required experimental data. Moreover, in section 4 a relation between the acquired sensory feedback and the bending angle measured using the vision system is derived using regression analysis and neural networks. The results obtained using both techniques are then presented, comparing the accuracy of their predicted bending angle values to the actual measured values. Furthermore, the derived empirical model and trained neural network are validated by evaluating their prediction accuracy when tested with new experimental data acquired at untrained operating conditions. Finally, the paper ends with some conclusions regarding the proposed sensing and modelling approach, highlighting the planned future work.

## 2.FABRICATION OF SOFT BENDING ACTUATORS

The main technique for fabricating SPAs relies on moulding silicone rubbers into the required shape, using 3D printed moulds with the negative of the features to imprint, followed by bonding the parts together after curing to create the final shape of the actuator (Ilievski et al., 2011). A soft finger based on a standard bending SPA design with ribbed channel morphology (shown in Fig. 1), was fabricated from a common silicone rubber material called (Ecoflex-50<sup>1</sup>). The dimensions of the soft finger were based on the results of previous work characterising the bending response and force generation of a set of soft fingers with variable internal channel dimensions (K. Elgeneidy et al., 2016). To fabricate the soft finger, it had to be divided it into three main parts (labelled on Fig. 1): (1) The main body moulded from Ecoflex-50 with the imprinted fluidic channel pattern, (2) the bottom base made also from EcoFlex-50 or a stiffer elastomer if desired, which seals the internal channels, (3) and a strain limiting layer in a form of a sheet of paper between those two parts. This layer is necessary to prevent the finger from extending, allowing only a bending motion curving towards its base. Here, we attach a flexible resistive sensor<sup>2</sup> to the strain limiting layer, in order to change in resistance as the soft finger bends without hindering the deformation process.



Fig. 1. A cross-sectional illustration through a typical bending SPA featuring a ribbed morphology.

The practical procedure involved in the fabrication of the soft bending fingers with embedded sensing can be summarised in the following steps:

- 1) *Printing Moulds*: The moulds with the negative of the geometry featured required to be imprinted, are designed and 3D printed from ABS filament.
- 2) *Mixing and Degassing*: EcoFlex-50 is prepared by mixing equal volumes of the provided components stirred well for 2 minutes. The mixed material is then quickly placed in a vacuum chamber at 900 mbar for about 5 minutes for degassing, in order to remove trapped air bubbles.
- 3) *Moulding*: the mixed material is then carefully poured in the 3D printed moulds to create the two parts of the soft finger with imprinted features, and then left to cure. The curing process can be accelerated by placing the moulds in an oven at 50° for around an hour.
- 4) *Strain limiting layer*: two pieces of paper are cut into the required dimensions to create the strain limiting layer which will fit between the two parts of the soft finger.
- 5) *Embedding flex sensor*: The flex sensor is positioned between those two sheets of paper and glued together to form one flexible but not extendable layer, to be embedded within the soft finger at the interface between the two moulded parts.
- 6) *Demoulding and Bonding*: both parts of the soft finger are demoulded and dipped in a freshly mixed EcoFlex material at their joining faces, to act as a bonding agent. The prepared strain limiting layer is placed on top of the base part, and the main body of the finger is then placed and aligned on top.
- 7) *Connection*: once bonding layer cures, a needle is inserted at the base of the finger to penetrate through the internal channels, which needs to be pneumatically actuated. A tube is then connected to the other end of the needle to be connected to the source of the pneumatic supply from the other end.

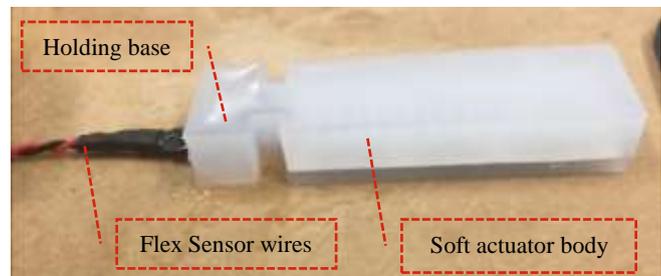


Fig. 2. Soft actuator sample with an embedded flex sensor

Although this process uses inexpensive materials and requires fairly simple equipment to implement, the manual nature of the process introduces sources of variation that could arise during the material preparation and moulding. This is one of the challenges faced in modelling the behaviour of soft actuators in general, due to the uncertainty in its dimensional accuracy and material properties, which encourages the data-driven modelling approach considered here.

### 3. EXPERIMENTAL TESTING

#### 3.1 Testing Platform

The next step after embedding the flex sensor within the soft finger samples is to create a setup that not only acquires the sensory feedback at controllable operating conditions, but also synchronises this with the corresponding bending angles measured during the actuation of the soft fingers. The developed testing platform comprises of the following units:

(a) A fixed frame setup with adjustable 3D printed mounts, which provides a modular interface that fixes the tested soft finger at desired orientations (measured from the positive X-axis) within its bending plane as show in Fig.3. The input pneumatic supply flows through a tube with a 1.6 mm needle attached to its end, to facilitate switching between finger samples easily during testing. The tip of this needle passes through a locating hole in the 3D printed fixture to pierce the soft finger at the base of the internal channels. The fixed inlet diameter for the needle means that the flow rate of the pneumatic supply can only be changed by varying the value of the input pressure and its duration.

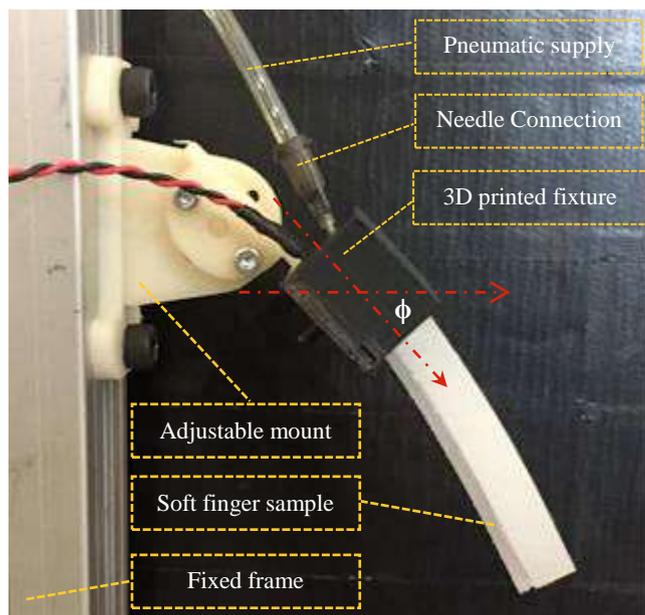


Fig.3. Experiment setup fixing the tested soft fingers

(b) A pneumatic control board, based on the design proposed in the soft robotics toolkit<sup>3</sup>, was built to control the actuation of the tested soft fingers. The board includes solenoid valves controlling the flow of pneumatic supply, pressure sensors measuring the output pressure at each channel, an Arduino microcontroller programmed to control the actuation process. The duration of each actuation as well as the input pressure can be controlled by setting the duty cycle and frequency of a pulse width modulated signal controlling the switching of the solenoid valves. Furthermore, the Arduino is interfaced with the on-board pressure sensors and embedded flex sensors, to

record and synchronise the sensory readings acquired during each actuation test.

(c) A high speed camera is used to capture continuous image frames at 130 Fps showing the deformation of the tested soft fingers upon actuation. The camera is fixed to the same frame that holds the soft finger, to ensure that it remains in the same location with respect to the fingers. Calibration for the intrinsic and extrinsic camera parameters was conducted to allow measurements in real-world coordinates for the radius of curvature, tip trajectory, and bending angle of the tested soft fingers. Furthermore, the camera is externally triggered via the Arduino microcontroller on the pneumatic control board, so that each captured image frame can be matched to the corresponding sensory readings recorded simultaneously.

#### 3.2 Acquiring Sensory Readings

Soft fingers were repeatedly actuated at different magnitudes and durations of the supplied pressure input, to confirm the repeatability of the sensory feedback. Fig. 4 shows a plot for the internal pressure measured against the resulting flex sensor readings, when supplied with a step pressure input of 12 Psi for different durations. The plotted cycle shows the value from the flex sensor decreasing upon actuation as the internal pressure builds up, until the pneumatic supply is stopped and the soft fingers starts to retract back to its original shape. The response was observed to be fairly repeatable; with longer actuation duration causing a systematic extension to the witnessed response. Thus, it can be assumed that when increasing the actuation duration, the soft finger will continue to bend following the same relation between the internal pressure and flex sensor readings, as long as the input pressure is held constant and the material does not fail.

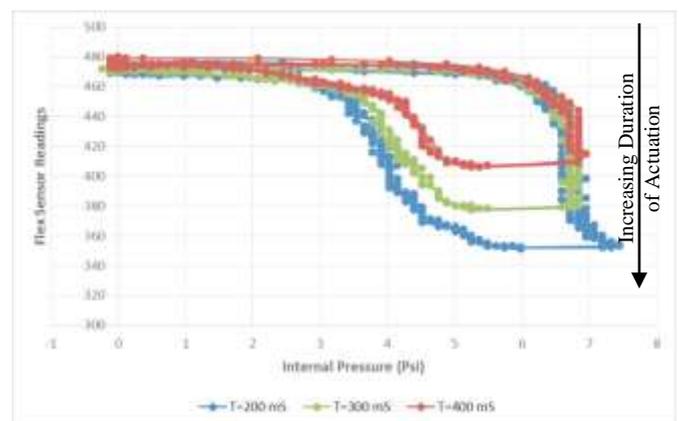


Fig. 4. Flex sensor response against the internal pressure at variable actuation durations.

Moreover, the same test was repeated again, but this time the actuation duration was fixed at 500 ms, while the soft finger was actuated using pressure inputs of 10 and 12 Psi. Fig. 5 shows that changing the input pressure had a more significant effect on the recorded sensory response, influencing not only the final reading from the flex sensor, but also the gradient of the response. The pressure input directly controls the flow

rate of the pneumatic supply energising the actuation. This shows the importance of incorporating the measured internal pressure response building up inside the soft finger during actuation, if accurate models are to be derived for the estimation of the bending response of soft fingers.

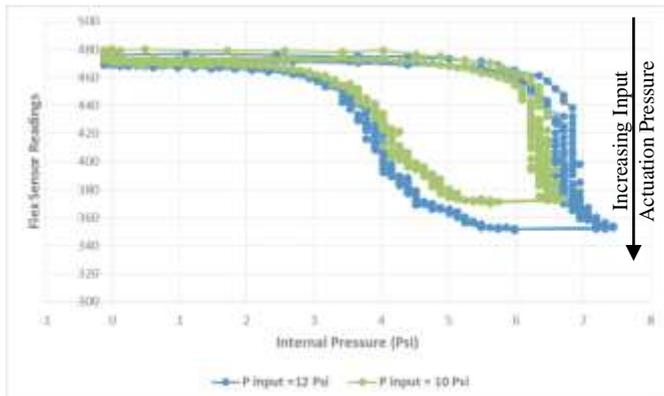


Fig. 5. Flex sensor response against the internal pressure at variable input actuation pressure.

Furthermore, Fig. 6 Shows the relation between the input pressure and flex sensor readings, at three different initial soft finger orientations of  $45^\circ$ ,  $0^\circ$ , and  $-45^\circ$  (measured from the positive X-axis). A deviation in the response can be observed in each case, especially during the retraction of the soft finger to its initial position, since the pneumatic supply is stopped and gravity becomes the dominant force acting on the finger. This shows the importance of taking the initial orientation of soft fingers into consideration when modelling their bending response, to be able to compensate for the effect of gravity and generate more accurate models (Polygerinos et al., 2015). The orientation here is known for each test since the tested soft finger is fixed using the 3D printed mounts, yet in actual grasping applications the orientation needs to be measured in real-time using an accelerometer sensor mounted at the gripper base. This would be an additional sensory input that can be interfaced to the main controller.

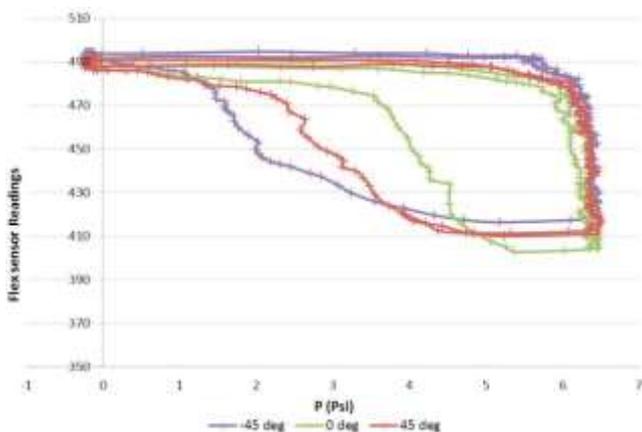


Fig. 6. Flex sensor response against the internal pressure at variable soft finger orientations.

### 3.3 Measuring Bending Angle

An image processing program was developed using Halcon library<sup>4</sup>, to process captured images for the actuation of fixed soft fingers, using a calibrated high speed camera. The aim is to track the trajectory of its fingertip and measure the change in bending angle, without using any external markers that could alter the bending response. To achieve this, the program segments the deforming soft finger body using automatic thresholding, aided with a dark background. Contours defining the circumference of the segmented blob representing the finger body are then extracted and processed to locate the position of the fingertip within each image frame in real-world coordinates. Afterwards, the bending angle ' $\theta$ ' is calculated with respect to the base of the soft finger as illustrated in Fig. 7, showing the output from the program.

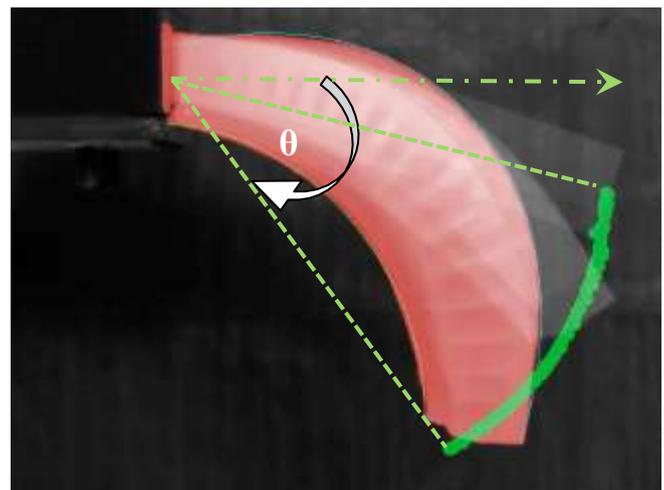


Fig. 7. Image processing program extracting the soft finger and tracking its trajectory to measure the bending angle.

## 4. DATA-DRIVEN MODELLING

The data acquired from the experimental tests would be utilised in deriving empirical models that describe the bending response of the investigated soft finger design. The input data comprises of the (1) internal pressure measured using on-board pressure sensors, (2) the change in resistance due to bending of the embedded flex sensor, (3) and the initial orientation of the soft finger known from the setup. A soft finger sample with embedded flex sensor was tested at three different initial orientations ( $-45^\circ$ ,  $0^\circ$ , and  $45^\circ$ ), using a step pressure input of 10 Psi and lasting for a duration of 400 mS. The finger was actuated twice under these input conditions at each of the tested orientations, while recording the generated sensory data and captured image frames to be processed for measuring the actual bending angle. Regression analysis and neural networks are two data-driven modelling techniques implemented and compared here, in order to derive empirical models that can be used in predicting the bending angle of soft gripper fingers, based on the generated sensory feedback. This can also be used as part of a control program to actuate the fingers to a specific bending angle.

4.1. Regression Analysis

First, we use linear regression to correlate the acquired internal pressure readings “P”, the embedded flex sensor readings “S”, and the initial orientation of the soft finger within its bending plane “φ”, to the actual bending angle “θ” measured using the developed vision system. The data set included 606 observations recorded as the soft finger fully actuates twice at three different orientations. The resulting empirical model (1) showed a good correlation between the inputs and outputs. The mean squared error (MSE) and standard deviation (SD) of the predicted bending angles for each finger orientation is shown in Table 1 below.

$$\theta = -185.51 - 0.166*P + 0.347*S + 0.991*\phi \quad (1)$$

Table 1. Regression error statistics at different orientations

|     | -45°  | 0°    | 45°   |
|-----|-------|-------|-------|
| MSE | 3.97  | 7.58  | 5.84  |
| SD  | 1.979 | 2.717 | 2.406 |

4.2. Artificial Neural Networks

A more advanced data-driven modelling technique investigated here is the use of artificial neural networks (ANN). The same data set used in the regression analysis was used again here to train a neural network with 1 hidden layer and 6 neurons. This network structure was found to reduce the MSE while avoiding overfitting. The inputs to the neural network are again the sensory feedback from the pressure and flex sensor, and the initial orientation of the soft finger, while the output is the predicted bending angle of the soft finger. To train the network, the measured bending angle using the vision system synchronised with the acquired sensory feedback, is used as target outputs. The training results showed a good fit between the inputs and target output as shown in Fig. 8, with improved accuracy compared to regression analysis as summarised in Table 2.

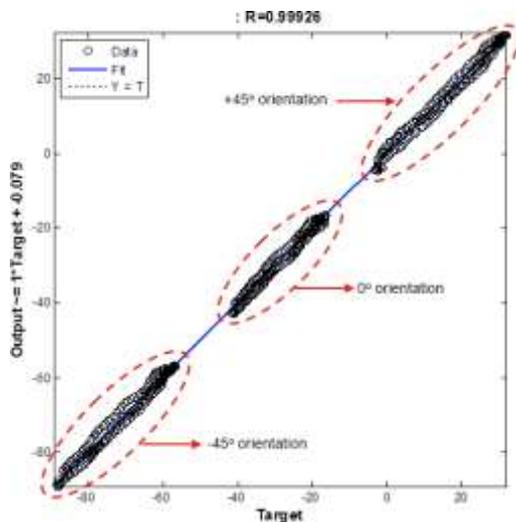


Fig. 8. Fitting the target outputs against the predicted values by the trained ANN

Table 2. ANN error statistics at different orientations

|     | -45°  | 0°    | 45°   |
|-----|-------|-------|-------|
| MSE | 1.52  | 1.60  | 2.12  |
| SD  | 1.231 | 1.262 | 1.449 |

4.3. Comparing the Prediction Accuracy

The accuracy of the derived empirical model using regression analysis and the trained neural network is evaluated by comparing their predicted values of bending angle to the actual value measured using the vision system. Fig. 9 shows that both techniques successfully reproduced the bending angle response at the tested finger orientations. It is obvious from comparing tables 1 and 2 that neural networks are able to generate more accurate predictions at the three tested orientations, with a notable reduction in the deviation from actual values. This means that the trained neural network was more successful in implicitly incorporating the effect of gravity at different orientations, and accurately captured the non-linear deformation of the silicone rubber materials used in fabricating the tested soft fingers.

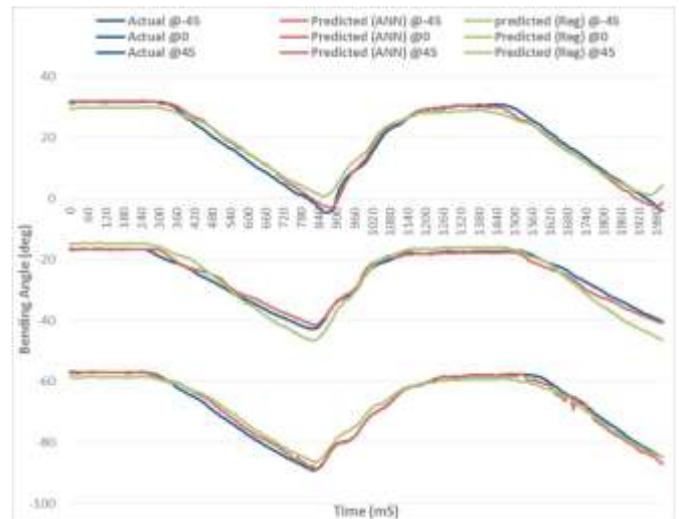


Fig. 9. Comparing the prediction accuracy of regression and neural networks

4.3. Validation and Discussions

Moreover, in order to validate the acquired results from both data-driven modelling techniques and safely assume they can be generalised to wider operating conditions, the prediction accuracy of the derived empirical model and the neural network were tested using a new data set acquired at different pressure input and actuation duration. A soft finger sample with the embedded flex sensor, was actuated at orientations of +45° and -45° at an input pressure of 12 Psi for a duration of 350 mS. The resulting sensory feedback was collected in conjunction with the corresponding bending angle measured using the vision system. The new data set was fed to the empirical model and neural network, and the resulting predicted bending angle was compared to the actual values as shown in Fig. 10.

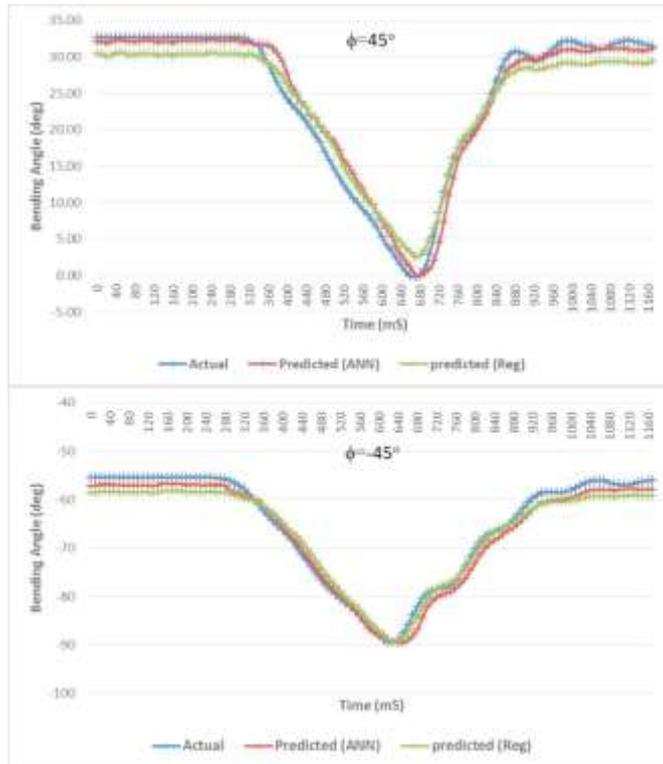


Fig. 10. Comparing the prediction accuracy of ANN and Regression using new input data at orientations of  $\pm 45^\circ$ .

It now becomes clear that both techniques can be used to predict the bending angle response when given new data sets acquired at untrained operating conditions. Again neural networks performed better than the derived model using regression analysis, as shown in the statistics in Table 3.

Table 3. Error statistics for the validation testing

|     | ANN   |       | Regression |       |
|-----|-------|-------|------------|-------|
|     | -45°  | 45°   | -45°       | 45°   |
| MSE | 13.18 | 10.93 | 15.53      | 14.72 |
| SD  | 1.207 | 1.71  | 1.855      | 2.10  |

### 5. CONCLUSIONS AND FUTURE WORK

The work presented here demonstrated an alternative approach for predicting the bending angle of a common soft pneumatic actuator using purely data-driven modelling techniques, which rely on generated data-sets of sensory feedback without the need for deriving complex physical and material models. A resistive flex sensor was embedded within the strain limiting layer of the soft actuator, which changes resistance as it bends with the bending of the soft actuator. While a pressure sensor connected to the pneumatic supply measures the internal pressures response during the actuation. The soft actuator was tested by fixing it to a testing platform at different orientations, and actuating it repeatedly with a controlled pneumatic supply. A high speed camera captures the deformation of the soft actuator and a developed image processing program tracks the tip trajectory along the image frames to measure the change in bending angle during actuation. Regression analysis and neural networks were considered as two common data-driven modelling techniques

that can be used to correlate the synchronised sensory feedback generated, with the measured bending angle output. Both techniques were successful in capturing the bending response of the soft actuator with neural networks providing more accurate predictions. In order to validate the derived models, a new data set was generated by testing the soft actuators at untrained operating conditions. The recorded sensory feedback was fed to both the derived model using regression analysis and the previously trained neural network, in order to compare their predicted bending angles to the actual values measured using the vision system. The error in the predicted values using both techniques increased, as to be expected when testing the models at untrained conditions. However, the response curves still managed to closely follow that of the actual bending angle values, with the neural network again providing more accurate predictions (Fig. 10). The main contribution of this paper is in the proposition of an alternative data-driven modelling approach that utilises feedback from inexpensive commercially available sensors to derive reliable empirical models, which can be used for prediction and control purposes. Another contribution is the inclusion of the effect of gravitational forces on the bending response, which is usually ignored when testing SPAs. This was achieved by supplying the initial orientation of the soft actuator as an additional input to the derived empirical models, to allow reliable predictions of the bending angles at different orientations. The results of this work showed that trained neural networks are able to predict the bending angle of this common design of bending SPAs at different operating conditions, despite the limited data sets used here in deriving those models. This shows the potential for generalising the use of the proposed approach with other SPA designs as long as the required sensory feedback can be generated. The main advantage of this approach lies lifting the need for prior knowledge about the geometry or material properties of the tested soft actuators. Instead, inexpensive commercial sensors can be used to provide the feedback required for deriving the empirical models, which implicitly incorporates variations in geometry and material properties that arise during the manual fabrication of such actuators.

This is part of ongoing work on developing more controllable versions of highly compliant soft gripper fingers, by providing them with sufficient sensing capabilities and intelligent controllers. The first stage of the work was presented here, demonstrating that a trained neural network is able to predict the bending angle of freely actuated soft fingers using simple sensory feedback. The next step is to develop a complete soft gripper prototype based on the soft fingers tested here, which uses trained neural networks to achieve more accurate manipulations. It is envisioned that by further training of neural networks under wider operating conditions, accurate estimations can be made about the position of the grasped object with respect to the gripper base, as well as detecting contact with the grasped objects and possibly monitoring this to predict slippage. This will provide a step towards expanding the application of soft grippers to include more complex manipulation tasks, which require not only the inherited softness and compliance, but also accurate position and force control.

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