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Research Article

Neural Network Based Inverse Modelling for Pneumatic Artificial Muscles

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Abstract

Pneumatic Artificial Muscles (PAM) are soft actuators with advantages such as high force to weight ratio, flexible structure and low cost. Pneumatic Artificial Muscles have inherent compliance that makes them feasible for exoskeletons and rehabilitation robots. However, their inherent nonlinear characteristics yield difficulties in modelling and control actions, which is an important factor restricting use of PAM. The compliance of PAM is associated with nonlinearity, hysteresis, and time varying characteristics, which makes it more difficult to model the dynamics and operation with model based high-performance controllers. Although there are many studies to overcome the modelling issue such as virtual work , empirical and phenomenological models, they are either much complicated or very approximate ones as a variable stiffness spring for model with nonlinear input-output relationship. Based on the analysis of well known previous modeling works in our PAM test bed, it has been observed that efficacy of the those methods are limited for representing the physical behaviour of PAM and thus there is still requirement for simple and effective models . In this work, apart from previous modeling approaches, the behaviour of PAM is foreseen as an integrated response to pressure input, which results in simultaneous force and muscle length change. Therefore, standard direct input-output identification methods are not suitable for modelling that behaviour. An inverse modeling approach is proposed in order to utilize it in control applications. The black box model is implemented by an Artificial Neural Network (ANN) structure using the experimental data collected from the PAM test bed. According to implementation results, an ANN based inverse model has yielded satisfactory performance deducing that it could be a simple and effective solution for PAM modelling and control .
Keywords: Soft Actuators, Pneumatic Artificial Muscles, Inverse Modeling, Artificial Neural Network Based Modelling.

Pnömatik Yapay Kaslar için Yapay Sinir Ağı Esaslı Ters Modelleme

Öz

Pnömatik Yapay Kaslar (PAM), yüksek kuvvet / ağırlık oranı, esnek yapı ve düşük maliyet gibi avantajlara sahip yumuşak aktüatörlerdir. Pnömatik Yapay Kaslar, dış iskelet ve rehabilitasyon robotlarında kullanımını mümkün kılan doğal bir uyumluluğa sahiptir. Bununla birlikte, doğrusal olmayan karakteristik özellikleri, modelleme ve kontrol eylemlerinde zorluklar sağlayan ve kullanımını kısıtlayan önemli bir faktördür. PAM doğal uyumluluğu, doğrusal olmayan, histerezis ve zamanla değişen özellikleri ile ilişkilidir, bu durum da PAM dinamik davranışını ve modele dayalı yüksek performanslı kontrolörlerle çalışmasını modellenmesini zorlaştırır. Literatürde modelleme sorununun üstesinden gelmek için, sanal iş, ampirik ve fenomenolojik modeller gibi birçok çalışma olmasına rağmen, bu çalışmalar çok karmaşık veya doğrusal olmayan değişken bir sertlikli yay için giriş-çıkış ilişkisi olan model gibi çok yaklaşıktır. PAM test düzeneğimizde gerçekleştirdiğimiz iyi bilinen önceki modelleme çalışmalarının deneysel analizine dayanarak, bu yöntemlerin etkinliğinin PAM'ın fiziksel davranışını temsil etmek için sınırlı olduğu ve hala basit, etkili modellere ihtiyaç duyulduğu gözlemlenmiştir. Bu çalışmada, önceki modelleme yaklaşımlarından farklı olarak, PAM'ın davranışı, giriş işareti olarak basınç uygulandığında, eşzamanlı kuvvet ve kas uzunluğu değişikliğine yol açan entegre bir sistem tepkisi olarak

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öngörülmüştür. Bu nedenle, standart doğrudan giriş-çıkış tanımlama yöntemleri bu davranışı modellemek için uygun değildir. Bu çalışmada, kontrol uygulamalarında etkin kullanmak için bir tersine modelleme yaklaşımı önerilmektedir. Önerilen kapalı kutu model ve PAM test yatağından toplanan deneysel veriler kullanılarak Yapay Sinir Ağı (YSA) yapısı tarafından uygulanmaktadır. Uygulama sonuçlarına göre, YSA tabanlı bir tersine model, PAM modelleme ve kontrol sorunu için basit ve etkili bir çözüm olabileceğini düşündüren tatmin edici bir performans sağlamıştır.
Anahtar Kelimeler: Yumuşak Eyleyiciler, Pnömatik Yapay Kaslar, Tersine Modelleme, Yapay Sinir Ağı Tabanlı Modelleme.

1. Introduction

The pneumatic artificial muscle (PAM) is a fiber braided and coated rubber tube actuator that changes its actuating length when pressurized . PAM was invented firstly by J. L. McKibben. It was redesigned by Bridgestone Company and used for some applications to assist disabled individuals. As compared to other conventional actuators (e.g.,motors, hydraulic actuators, and penumatic cylinders), PAM could be foreseen more similar to the human muscle in behaviour. Pneumatic Artificial Muscles (PAM) are type of actuators that mimic behavior of skeletal muscle by contracting and generating force in a nonlinear manner when pressurized. PAM has a radially inflation and axially contraction behavior which produces high pulling(tensile) forces along the longitudinal axis. It has low weight, and high power/weight output. Moreover, the PAM has inherent compliance that makes it feasible for exoskeletons and rehabilitation robots. (Daerden & Lefeber 2002).

However, the compliance of the PAM is associated with nonlinearity, hysteresis, and time varying characteristics, which makes it more difficult to model the dynamics and design high-performance controllers. A detailed survey of McKibben PAM modelling approaches is given by Tondu. (Tondu 2012). Furthermore, the dynamic models of the PAM may be grouped into two classes, a theoretical model and a phenomenological model, respectively (Kelasidi et al 2012). The theoretical model describes the relationship between the PAM's characteristics and the parameters directly related to the PAM's geometric structure and material properties, that has a complex structure with many parameters. For example, Chou and Hannaford derived the model from the law of energy conservation, and described the relationship among the pressure, the length, and the contractile force of the PAM (Chou and Hannaford 1996). The phenomenological model, on the other hand, is constructed according to the relationship between the input and output of the PAM, and is suitable for very complex dynamics that are hard to describe by the theoretical model. Among the phenomenological models of the PAM , the most used one is the three-element model proposed by Reynolds, in which the PAM is considered as a parallel arrangement of three elements (Reynolds et al 2003). However, both the theoretical and the phenomenological models contain time varying parameters and non-modeled uncertainties that need to be compensated by control techniques. Due to the nonlinearity, hysteresis, and time-varying characteristics of the PAM, it is difficult to precisely describe its dynamics in the entire range of pressure using only one model with constant parameters. (Zhang et al. 2016). The model-based schemes usually cannot obtain high-precision control due to the errors between the actual PAM dynamics. In addition, an emprical modelling approach is given by Wickramtunge and Leephakpreda which relates force and muscle legth as a nonlinear elastic relation . (Wickramtunge and Leephakpreda 2013). Martens et al. , in their work, performed a comparative analysis of the existing static models developed for Festo PAM. (Martens and Boblan 2017). Moreover, Ishikawa et al. also performed model parameter extraction of structurally different PAMs using SVM. (Ishikawa et al. 2018).

There are many studies to overcome the modelling issue in literature, such as virtual work , empirical and phenomenological models, AI based models. NNARX based modelling approaches is given by Ahn et al. (Ahn et al 2008). A hybrid ANN approach is developed by Song et. al. (Song et. al. 2015). A recurrent Neuro-Fuzzy based model is introduced by Chavoshian et al. (Chavoshian and Taghizadeh 2020). However, they are either much complicated or very approximate ones as a variable stiffness spring for model with nonlinear input-output relationship . Majority of the existing methods are standard direct pressure input and force output models.

In this work, initially an experimental analysis for characteristics of PAM has been performed using a test bed. Based on the analysis of some well known previous models using our PAM test bed, it has been observed that efficacy of the those methods are limited for representing the physical behaviour of PAM due to fact that models mostly concentrate direct input-ouput relation in terms of pressure and force estimation. In many existing models, the integrated response behaviour of PAM is not combined effectively in terms of simultaneous resultant force and muscle contraction. Hence, we deduce that there is still requirement for simple, effective models . By this foresight, apart from previous modeling approaches, the dynamic behaviour of PAM is modelled as an integrated response to pressure input, which results in simultaneous force and muscle length change. In this case, standard direct input-output identification methods ,such as NNARX, are not suitable for modelling that behaviour. Furthermore, an inverse modeling approach is proposed in order to utilize the model in control applications. The black box model is implemented by an Articifial Neural Network (ANN) structure using the experimental data collected from the PAM test bed.

The rest of the paper as follows: In section II, the implementation method is given, where experimental setup and data acquisition , modelling approach are explained. In section III, experimental results and discussions are presented. In section IV conclusions are drawn.

2. Material and Method

Nowadays, PAM is produced commercially by Festo Company and it is also called Festo fluidic muscle. The Festo muscle is structurally different from the general McKibben muscles. The fiber of the fluidic muscle is knit into the rubber tube, offering easy assembly and improved hysteric behavior and nonlinearity compared to conventional design (Festo 2018). Due to difference in construction, Festo PAM have different properties as compared to other existing PAM models. In figure1, a DMPS20 series Festo fluidic muscle and its dynamic characteristics is illustrated. In figure 1, F indicates the generated force by PAM in N and h indicates percentage muscle length change in terms of contraction [3] or extension [4], against different applied pressure curves.

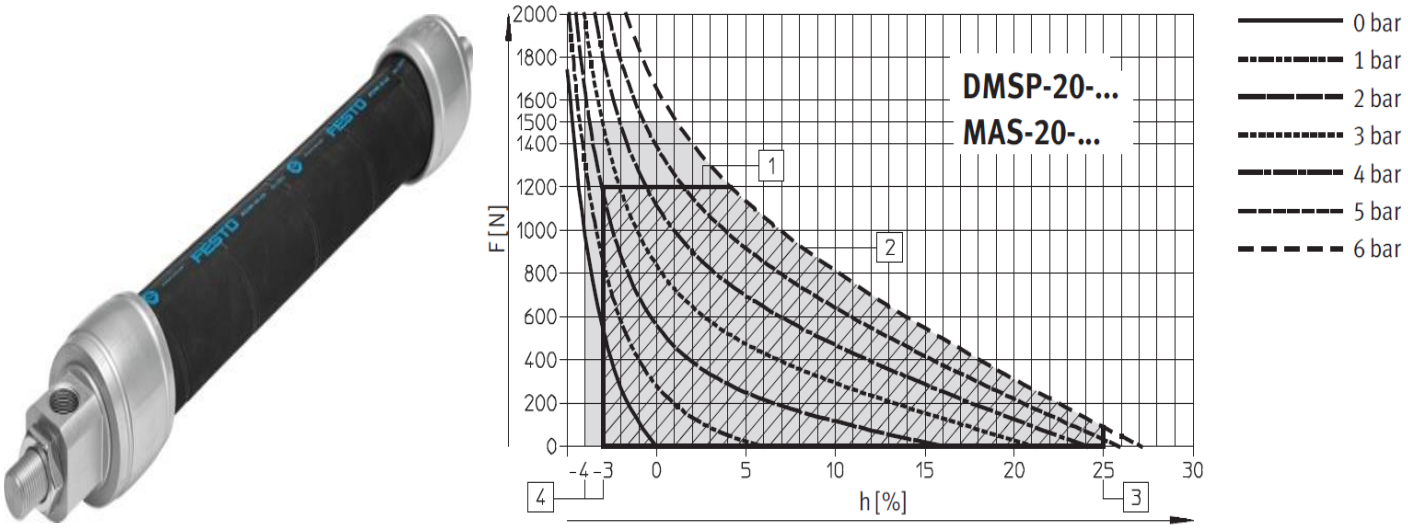


Figure 1. Festo Fluidic Muscle and Dynamic Characteristics (Festo 2018)

An experimental analysis has been performed for physical characteristics of Festo PAM, using a hardware test bed. When the dynamic characteristics analyzed, it has been observed that PAM had different operating curves for different applied pressure values which is also a confirmation of manufacturer's curves. Those different operating curves is the main cause for nonlinear behaviour of PAM. During the analysis, it has been observed that although applied pressure was the only input, but there was an integrated response of generated force and muscle length change as the output. In the test bed experiments, data has been obtained for different input pressure values and with different external loads. During the experiments, data from test bed has been obtained and compared to Matlab simulation results of some well known models. It has been concluded that majority of existing modelling approaches includes muscle length but considers solely force as the ouput. However, in our case, when PAM used as actuator, both force and muscle length have become equally important. Hence, in this work integrated response approach has been implemented as inverse modelling approach.

2.1. Overview of Main Modelling Approaches

In this section, as a starting point, main PAM modelling approaches in literature has been briefly introduced in order to illustrate the differences. In the modeling works, the main purpose is to establish a relationship between pressure, extension of the muscle along the entire axis (displacement) and force. Pulling force, air pressure, diameter and length of the muscle, material properties play an important role in modeling approaches. PAM's mathematical models relate these factors (Kelasidi et al.,2011). In general, modeling approaches depend on the static and dynamic behavior of PAM.

When developing a static model of the muscle, the basic approach is based on energy modelling. That approach provides a relationship between "actuator force, pressure and length", showing the length or degree of contraction and the diameter of the muscle formed by the forces, the actuator performance, taking into account virtual work and energy savings. The Chou and Hannaford model is the simplest geometric model for the static performance of a PAM (Chou and Hannaford,1996). In their approach, PAM actuator is modeled as a cylinder and the equation showing the expression between pressure, position and pressure according to this model is as follows. In the equation 1,b is the thread length. n indicates the number of turns of a thread. θ angle is defined as the angle between longitudinal axis and thread.

$$\boldsymbol{F = P' \frac{b^2}{4\pi n^2}(3cos^2\theta - 1)} \qquad (1)$$

The aim of the dynamic model, also known as the phenomenological model of PAM, is a simple approach to evaluate the dynamic behavior of the pneumatic muscle. In dynamic modeling, as seen in Figure 2, the parallel configuration of the muscle, spring, damper and contractile element is used. the coefficients corresponding to these three elements depend on the input pressure of the PMA (Reynolds et al., 2003).

$$\boldsymbol{M\ddot{x} + B(P)\dot{x} + K(P)x = F(P) - Mg} \qquad (2)$$

In equation 2, **M** is the load mass , **g** denotes the acceleration of gravity. **K(P)** indicates the spring coefficient. **B(P)** is damping coefficient and it depends on whether the PAM being inflated or deflated. **F(P)** is the effective force provided by the contractile element. The details for coefficients could be found in the work by Xing (Xing et al 2010).

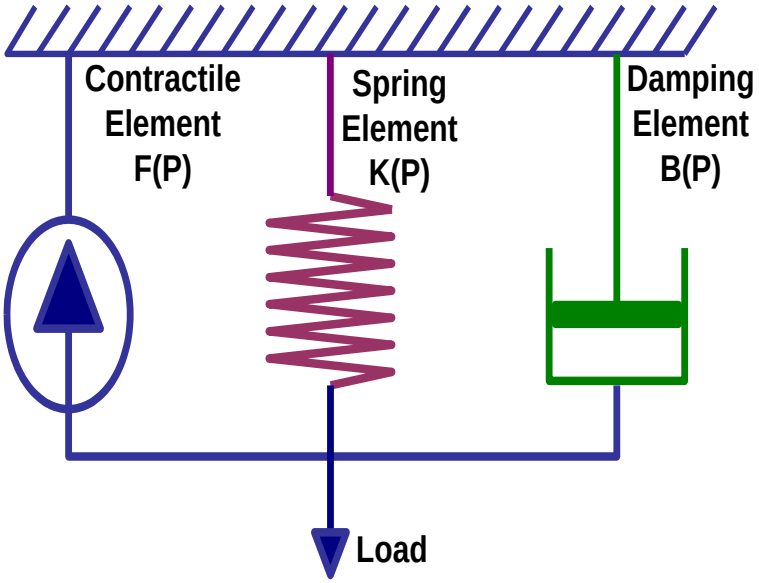


Figure 2. Three Element Phenomenological Model of PAM

2.2. PAM Test Bed Hardware Implementation and Data Collection.

Pneumatic Artificial Muscle Test Bed that has been used to perform experiments is shown in figure 3. The corresponding labels for the components of harware are given as follows: Electronic Interface and Data Acquisition Module is indicated with label I. Bourne AMS22 type encoder labeled with II is used for the muscle active length measurement. The pneumatic artificial muscle (PAM) indicated with III is the DMSP 20 series of Festo and that could work in the range of 0-7 bars , with a length of 250 mm. Label IV marks Honeywell 24PCF series pressure sensor operating in the range of 0-8 bar. Label V shows Matrix MX890 series very fast on/off valves of used with PWM drives. For the force measurement , Zemic H3-P3 S type load cell with 0-100 kg range is used.

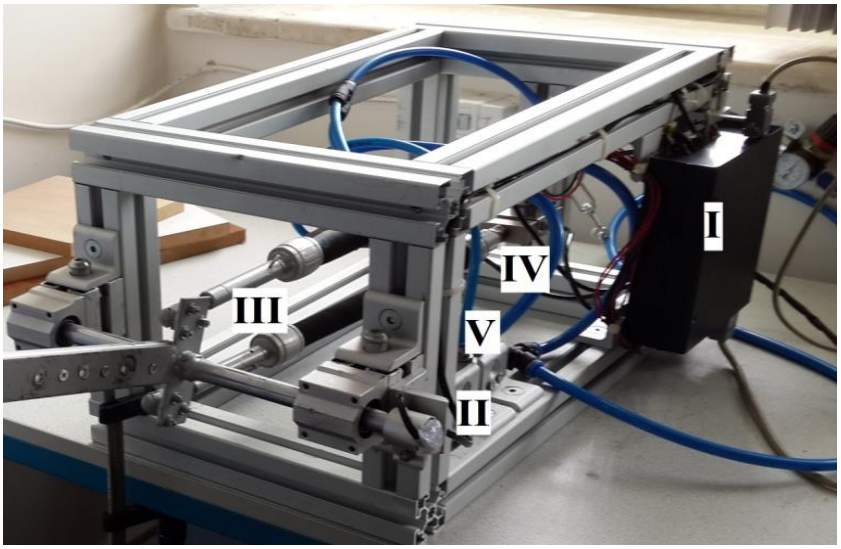


Figure 3 Pneumatic Artificial Muscle Test Bed

During the experiments, MATLAB /Simulink blocks are used to implement data acquisition software for sensors and actuator configurations and closed loop controllers. The Simulink blocks are compiled and sent to a microprocessor running in "Data Acquisition" unit. In the test bed, ATMEL Arm Cortex M3 microprocessor card is used to control the system. Initially, the accuracy of our PAM test bed is checked by the emprical modelling experiment and hence we obtained very similar results to that non-linear elastic relation expressed by Wickramtunge et al. After that, we have concluded that the performance of our test is satisfactory. (Wickramtunge and Leephakpreda 2013). The experiments has been performed using 0.05 Hz sinusodial reference curves with PID pressure control in order to obtain data to be used in modelling. The slow pressure reference has been chosen to understand quasi-static characteristics of PAM. The collected data used in Matlab for ANN toolbox.

2.3. Neural Network Implementation.

In this work, in order to model the dynamic behaviour of PAM as an integrated response to pressure input, an Artificial Neural Network was chosen and implemented by using Matlab ANN Toolbox. ANN is a basic MLP with 1 hidden layer composed of 20 neurons. ANN was trained with Levenberq-Marquardt algorithm. Structure of ANN is formed by empirical manner. Overall block diagrams of ANN is given in figure 4 and 5. The experimental data in terms of force, muscle length and pressure was collected from the PAM test bed and has been used for training and testing ANN. As an inverse relation, the force data and muscle length data were used as inputs to ANN and pressure value was used as desired output for training and for performance analysis. Training and testing performance of ANN is given in figures 6 and 7. Regression results indicate that ANN is successfully trained and tested.

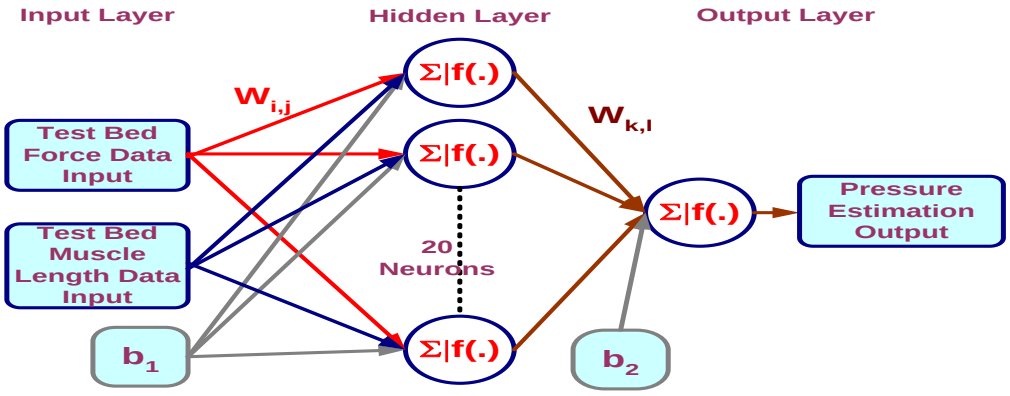


Figure 4 Block Diagram of Implemented ANN

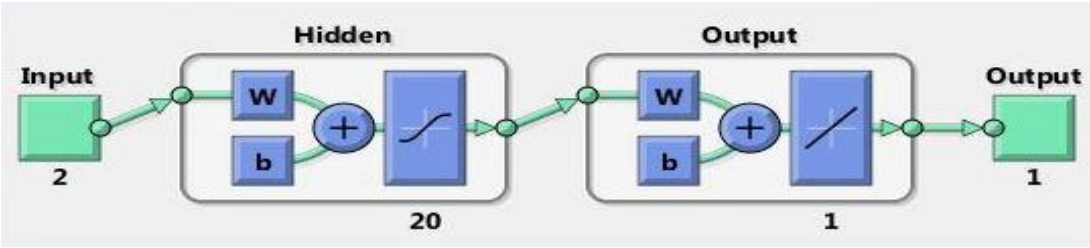


Figure 5 Matlab Block Diagram of ANN

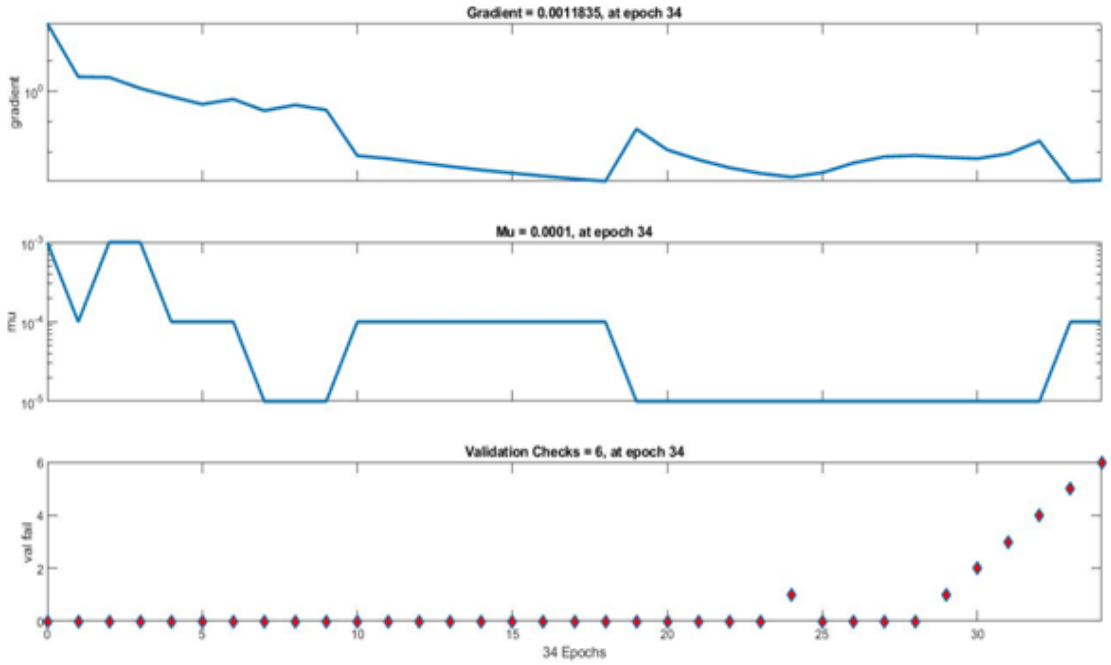


Figure 6 Training Performance of ANN

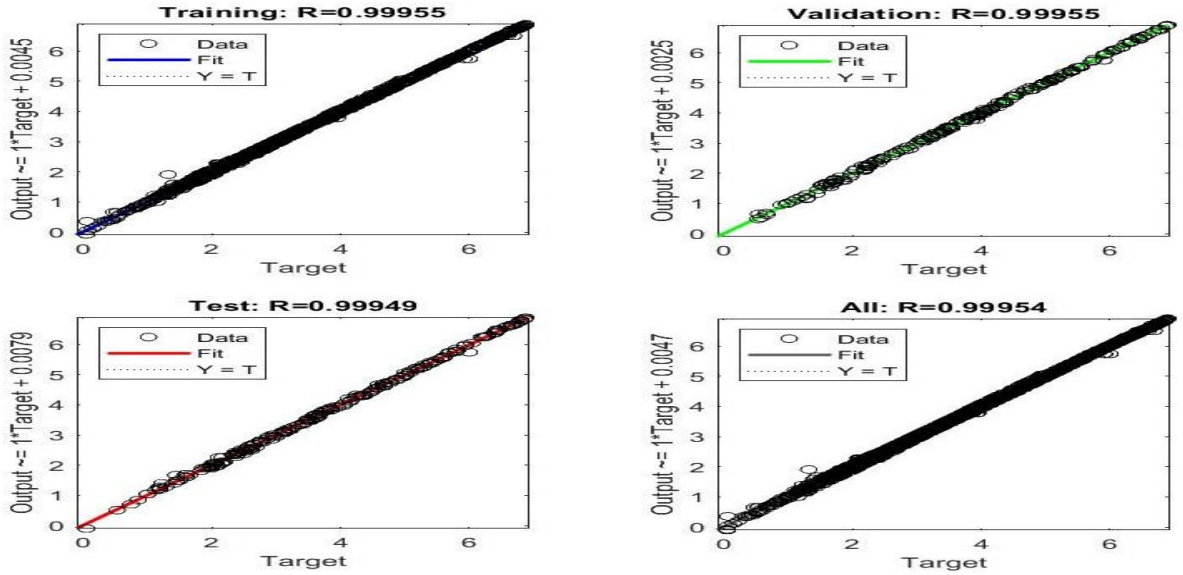


Figure 7 Testing Performance of ANN

3. Results and Discussion

After having the ANN successfully implemented and trained, three other data set has been used for performance analysis. The ANN has been transformed into a Simulink model as shown in figure 8. Different data sets are generated from PAM test and has been fed to ANN model test in Simulink. Data generation was performed by applying a closed loop PID pressure control on PAM test bed with a 0.05Hz sinusoidal reference signal varying in 0-7 bar, with the test bed under different loads in range of 15-100 kg. During the data generation, a full range of muscle contraction (25 %) and extension (5 %) has been reached for the muscle length variation. A random mixture of data is formed as Input-Output vectors by a common sequence index in Matlab. The force and muscle length data vector is applied as inputs to ANN where as pressure values are used for performance comparison. For performance analysis, the output pressure estimation of ANN has been compared to experimental pressure values from new data set. In figure 9, the first data set composed of 85 item vectors is applied to ANN model and the resultant performance occured as quite satisfactory with an error of maximum 5-8 %. In figure 10 a similar performance has been observed with another test data set. Moreover, another data set generated by using a faster reference signal which is 0.5 Hz is also applied for longer run. Figure 11 indicates the performance of ANN for this long run data set. However, percentage error for the fast reference performance has increased due to effect of fast switching on-off valves during data generation. To conclude, those performances indicated that a simple ANN could be used as a transforming and

mapping control block between high level and low level. A high level desired actuator position in terms of muscle length and a simultaneous force generation demand has been mapped into a low level pressure set value to be used in PID pressure control loop for PAM.

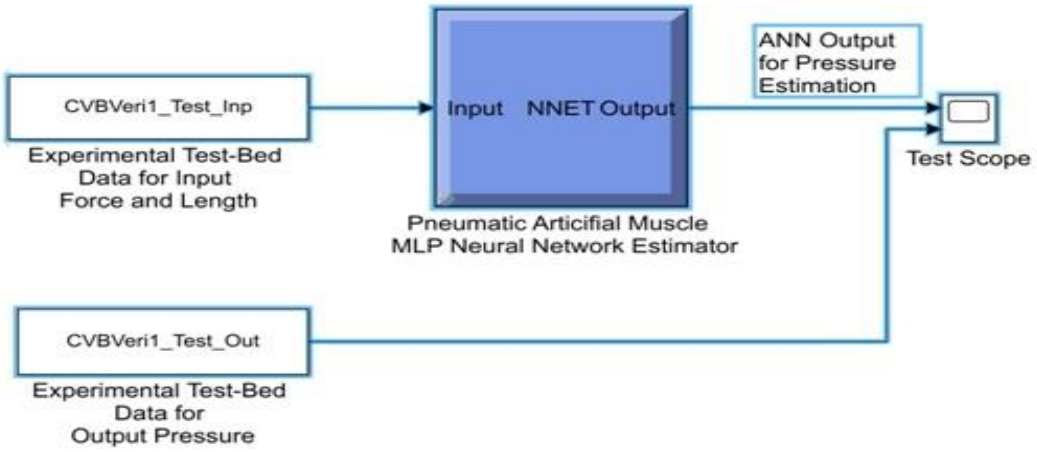


Figure 8 Simulink Performance Test Application

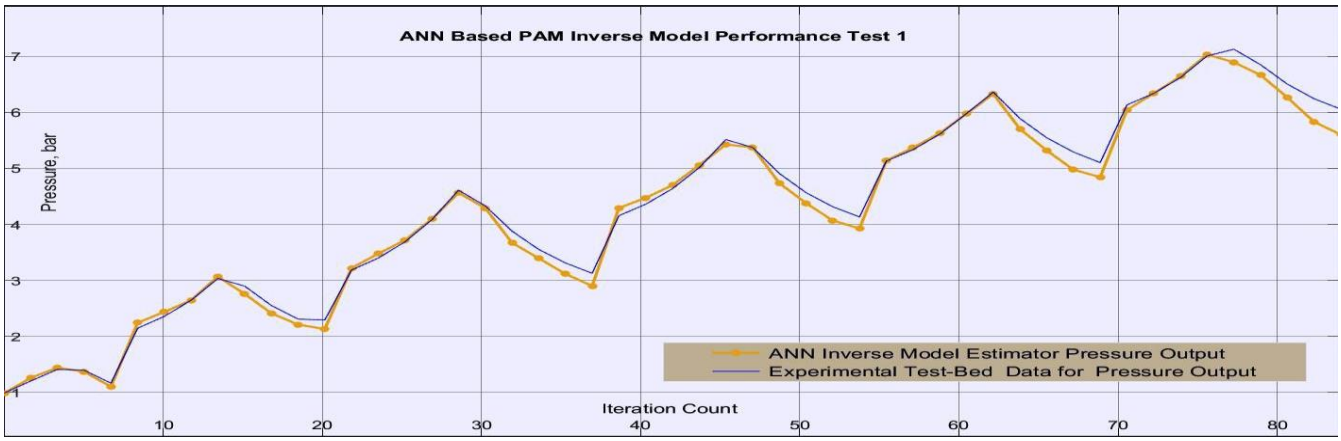


Figure 9 ANN Performance Test Result #1

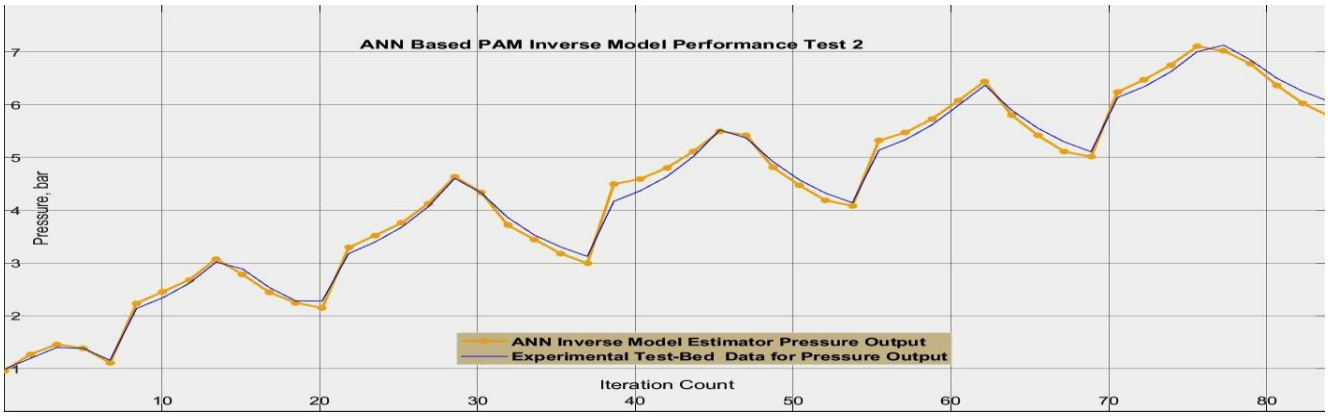


Figure 10 ANN Performance Test Result #2

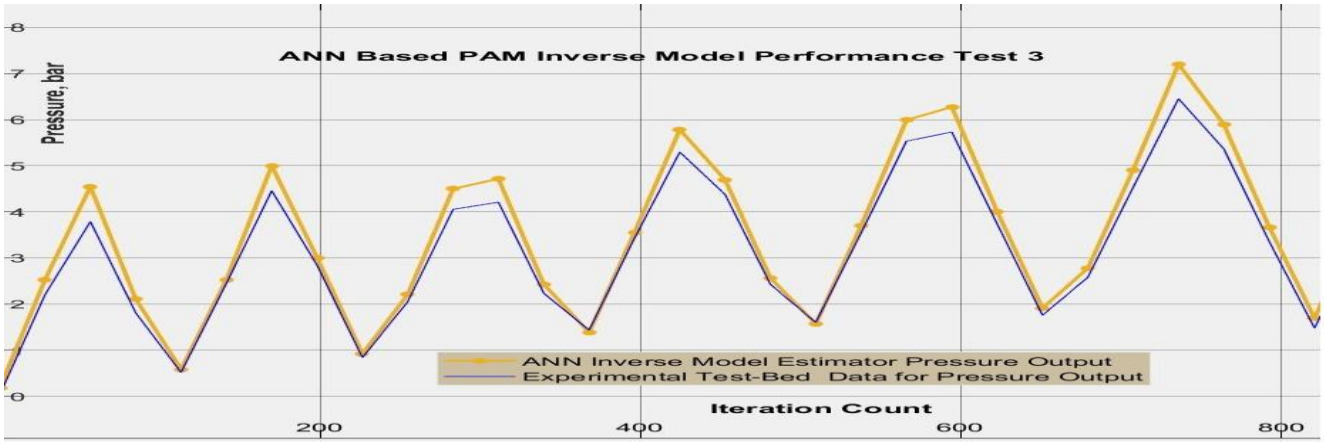


Figure 11 ANN Performance Test Result #3

4. Conclusion

In this work, apart from previous modeling approaches, the behaviour of PAM is foreseen as an integrated response to pressure input, which results in simultaneous force and muscle length change. Therefore, standard direct input-output identification methods are not suitable for modelling that behaviour. An inverse modeling approach is proposed in order to utilize it in control applications. The black box model is implemented by an Artificial Neural Network (ANN) structure using the experimental data collected from the PAM test bed. According to implementation results, an ANN based inverse model has yielded satisfactory performance deducing that it could be a simple and effective solution for the PAM control in terms of high level to low level mapping.

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