Machine Learning based Self-sensing the Stiffness of Shape Memory Coil Actuator

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Machine Learning based Self-sensing the Stiffness of Shape Memory Coil Actuator

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Abstract— Self-sensing actuation (SSA) assists in sensing the vital property of the shape memory coil which can be used to monitor and control the actuation. The stiffness characteristic of the shape memory coil is sensed during actuation which plays a significant role in development of Intelligent Robotics in defense systems. The electrical property of shape memory coil such as electrical resistance changes due to martensitic phase transformation which is further used to sense the mechanical properties such as strain, stress, temperature, length, and force. Nowadays electrical properties are used to sense the stiffness of the shape memory coil. As of now, there is no well-established analytical model to predict the stiffness of sensing during actuation accurately. Therefore, Machine Learning (ML) based data-driven intelligent model is proposed in this paper for auto-sensing of the stiffness. The experimental facility has been developed for the collection of data with respect to diverse Joule heating currents. To determine the experimental data values of stiffness and electrical resistance of shape memory coil is a cumbersome task. Hence we have proposed an automated method to predict the stiffness of the shape memory coil using ML methods. The Classical Polynomial and Feedforward Neural Network (FFNN) models are developed for analyzing the stiffness of the shape memory coil. It is found that FFNN model outperforms the other ML based model by attaining 95.2650 % accuracy. The FFNN model is also able to explain almost all the predicted stiffness values which are experimentally recorded. The FVU (Fraction Variance Unexplained) statistical parameter explains the prediction of FFNN with the value of 0.0842. The great advantage of the ML model is to replace two sensors (Force and displacement sensors) with one soft sensor (ML model). It will be useful in the controlling robotics and other devices which require high precision in data generated by the sensors.

Keywords— *Shape memory coil, Joule heating, Stiffness, Self-sensing actuation, Machine Learning (ML), Feedforward Neural Network (FFNN).*

Declaration:

1. Introduction

In an intelligent Robotics and bio-engineering system, an active structure is needed that can change their mechanical characteristics and transfer their action to the passive structure (Keene Chin et al. 2020). The large force and controllable stiffness of Shape Memory coil can be used to solve the problem of actuation and for sensing the passive mechanical structure. The shape memory coil provides the actuation to a passive mechanical structure and to the resistance of the coil to sense the stiffness with variable load in the structure. Therefore it can be inferred that the Shape Memory coil with flexible stiffness is one of the effective solutions (Bhagoji Bapurao Sul and Dhanalakshmi K 2018, 2019) to design automated tools. The self-sensing of varied stiffness actuation plays a vital role in designing the robotics in defense systems. Sensing the stiffness of

the mechanical structure directly is quite difficult. As of now there exists no efficient analytical model for self-sensing the variable stiffness actuation. The ML based self-sensing of shape memory coil can be utilized in these fields to do high quality sensing and actuation work in Shape memory coil. The FFNN algorithm with optimized model is an effective as well as efficient method to self-sensing of variable stiffness actuation of shape memory coil.

The resistance estimates the stiffness, a nonparametric model (ML based FFNN) developed with a finite set of experimental data. To decide the external parameter (hyperparameter) such as learning rate and number of hidden layer neurons are difficult tasks and can be solved by Bayesian search. The Bayesian search is the optimization technique of ML that can find the optimum hyperparameters (learning rate and number of hidden layer neurons) of FFNN. So self-sensing of Shape memory coil by ML can be the suitable alternative to the mention problem (Ong Hong Choon et al. 2008).

FFNN models are enough flexible and useful when there is no prior knowledge of system applications. The estimation of change in stiffness due to resistance change is an inherent property of shape memory alloy due to the shape memory effect phenomenon. This inherent property comprises a reversible crystalline phase transformation between the austenite and martensite phases. These two phases have different crystallographic structures but with the same chemical composition, atomic weight, and mass number. The Feedforward Neural Network (FFNN) model is compared with the classical regression polynomial model and the results obtained from FFNN are promising (Angelo Alessandri et al. 2009).

1.1 Background and Literature Review

The electrical resistance of Shape memory coil changes when it regains its original (parent) shape, and this was proved during 1990 (Koji Ikuta 1990). This change in Electrical resistance property leads to development of Shape memory coil as a sensor during actuation. Later on, many researchers proved that SMA is useful in sensing the thermal and mechanical properties of its own and other object (N. Ma et al. 2004; H. Gurang and A. Banerjee 2016; Chao-Chieh Lan and Chen-Hsien Fan 2010; Estibalitz Asua et al. 2010; Pavanesh Narayanan and Mohammad Elahinia 2016; Austin Gurley et al. 2017; Yasuyuki Suzuki and Y Kagawa 2019). The electrical resistance is changing nonlinearly with contraction of length of SMA wire. So, it is suggested that Neural Network handle nonlinearity better and used to model the relation between resistance and

contracted length of SMA wire (N. Ma, et al. 2004). The Unscented Kalman Filter (UKF) estimates the contracted length as a state with help of measured electrical resistance of SMA wire actuator. The SMA wire actuator is heated by joule heating with different voltages and state of SMA estimated by UKF will take 50% less time for computation as compared with Extended Kalman Filter (EKF). The UKF model developed the state estimation of contracted length to harness the self-sensing capability of SMA wire. It reveals the true potential of UKF model of self-sensing capability by comparing with experimental response (H. Gurang and A. Banerjee 2016). The self-sensing of strain of SMA wire by Polynomial Model and it is utilized in the feedback to control the motion of flexure. It is proved that larger/sufficient the pretension force; straighten the cooling path and inaccuracies are overcome by reducing the hysteresis gap. The self-sensing strain characteristics is independent of bias spring stiffness and environmental temperature (Chao-Chieh Lan and Chen-Hsien Fan 2010). To characterize the self-sensing of position of SMA wire; Neural Network method is better than first order equation and able to obtain the accuracy of 50 µm. The great advantage of this method is that it is without sensor. Hence this method will reduce the overall size, weight and becomes compact (Estibalitz Asua, et al. 2010). The Artificial Neural Network model to map the self-sensing of rotary position of manipulator and electrical resistance of SMA wire. The Self-Sensing ANN model predict the rotary position accurately up to minimum of 0.8º. The proposed self-sensing model is robust with respect to environmental temperature variations from -5 ºC to 45 ºC. The performance of model is sensitive to pre-stress and load on manipulator (P. Narayanan and Mohammad Elahinia 2016).

The innovative way to find the electrical resistance of SMA wire for self-sensing of wire position. The innovative way is that it gives direct contracted length by measurement of two voltages across the SMA wire: one voltage across complete wire and other across fixed length of SMA wire. The error in sensing the contracted length of SMA wire is less than 0.5 mm of true length (Austin Gurley et al. 2017). The Dynamic tracking control of an SMA wire actuator based on model matching is used to understand the self-sensing of force. The force is used to control the deformation of SMA wire actuator which is self-sensed and based on first order approximation. The first order approximation of force is improved by using H-infinity controller. This is verified by comparing H-infinity based system and a solely PI-controlled system. This work suggesting that creation of compact self-sensing actuator is viable (Yasuyuki Suzuki and Y Kagawa 2019). The shape memory spring used as a sensor to position/displacement and stiffness which is mathematically related by

linear equation and depends upon phase transformation. The resistance of SMA varies according to phase transformation and it is decreasing from martensite phase to austenite phase, since it is high in martensite phase and low in austenite phase (Makoto Kumon et al. 2007).

The stiffness of SMA spring is control through electrical resistance, position feedback and sensor-less sensing of force. The resistance is changed during phase transformation and simultaneously stiffness of SMA spring changes. The resistance change can be used to monitor the phase transformation and improve the robustness of heat disturbance to avoid overheating of SMA spring. So, the stiffness and resistance are linearly dependent and can be used to directly control the stiffness (Koji Ikuta 1990). The self-sensing modeling and investigations of stiffness characteristics of SMA spring. The stiffness depends not only on joule heating activation current but also on excitation frequency. The experiment confirmed that stiffness is sufficiently linear with joule heating current and excitation frequency. Hence it can be used to control the stiffness of passive structure with these parameters (Bhagoji Bapurao Sul and Dhanalakshmi K 2018).

The modified new mathematical function relating the stiffness and temperature of SMA spring and hysteresis characteristics between them can be control by electrical parameters such as current, frequency and pre-stress. The mathematical function of stiffness is verified with experimental data (Bhagoji Bapurao Sul and Dhanalakshmi K 2019). The nonlinear hysteresis characteristics between displacement and temperature are controlled through electrical and mechanical parameter. The ANN is the best tool to map hysteresis characteristics effectively between any two properties of SMA spring successfully and verified with experimental data (Bhagoji Bapurao Sul et al. 2018).

This work helps the research scholars/users to create calibration equations from basic calibration data and use these equations to make accurate measurements. The appropriate mathematical model of sensor characteristics can be obtained by curve fitting (Boyanka Marinova et al. 2009). The comparison between classical polynomial regression and Feedforward Neural Network (FFNN) methods of modeling concludes that complicated interaction function can be better model by the FFNN method (Angelo Alessandri et al. 2009). The Neural Network universal approximator which is performing better than polynomial regression explained correctly in (Ong Hong Choon et al.2008). The progress report of how Machine learning is useful to such a system whose mathematical / analytical function is not known exactly is reported by (Keene Chinet al. 2020).

The focus of (N. Ma et al. 2004; Estibalitz Asua et al. 2010; Pavanesh Narayanan, Mohammad Elahinia 2016) is only on Neural network based self-sensing to position/contracted length/displacement of SMA wire/coil modeling but not on the optimization of the model used. The self-sensing of the displacement/force of SMA wire done by conventional way of modeling in (Austin Gurley et al. 2017; Yasuyuki Suzuki and Y Kagawa 2019). The different curve fitting equations are used to model the sensor characteristics and determine the best out of it for calibration in (Boyanka Marinova et al. 2009). The any mathematical function can be model by universal approximator (FFNN) and it is called white box modeling in (Angelo Alessandri et al. 2009; Ong Hong Choon et al. 2008). But it could not explain how to optimize it. The progress review of data-driven model by machine Learning which is called black box modeling for sensing, actuation and control is in (Keene Chin et al. 2020).

Major highlights of the research work

1) The optimized data driven model of self-sensing the stiffness of shape memory coil actuator is Designed and developed.

2) Feedforward Neural Network (FFNN) is optimized by Bayesian search in order to achieve the objective of this research work.

3) FFNN based data driven model provides 95.2650% accuracy and outperforms classical Polynomial model (90.5844%).

4) The FFNN based soft sensor eliminates two physical sensors (Force and Displacement sensors) for measurement of varied stiffness actuation of mechanical structures.

6) This soft sensor can be used for structural health monitoring (SHM) online as well as offline.

7) The self-sensing variable stiffness actuation can be applied in many defence based applications such as robotics, structural health monitoring and defence equipment.

The paper's description started with an introduction, background, and a review of referred papers relating to stiffness, self-sensing, and modelling of the Shape-memory coil actuator. Section 2.0 explains the hardware components, experimentation, circuit operations, and experimentation details. Section 3.0 explains information about the methodology of the classical Polynomial model

and FFNN with its optimization by Bayesian search. Section 4.0 describes the experimental results and discussions on results. The modeled and experimental characteristics are compared with both methods and verified for Joule heating current. Section 5.0 provides summary on the proposed FFNN hybrid approach.

2. Experimentation and Circuit Operation

The data-driven model needs enough experimental data to model the characteristics between stiffness and resistance of shape memory spring. Hence experimental facility and conduction of experimentation are essential. The experimental setup consists of an actuation system, Joule heating circuit, Power supply, and data acquisition system with its arrangement and it is in the photograph of Fig.1.

The actuation system consists of a shape memory coil biased with an antagonistic tensile spring without obstacle and free movement of both the spring with guide rod. The Joule heating circuit has different components such as a power transistor to heat the coil, one quarter watt resistance in the base to make transistor on-off, one 40-watt rheostat to find the accurate resistance of the SMA coil and required power supply. The D.C. regulated power supply, dual power, and A.C. power supply are essential to operate the circuit. The data acquisition system includes mainly a miniature force sensor, laser displacement sensor, current sensor, measurement of voltage across SMA coil, and the voltage across rheostat. The various signals from such sensors and SMA coil are sent to signal conditioning circuits and some, goes directly to the data acquisition card so that it should be compatible with the data acquisition system for proper record into the computer memory. The shape memory coil is purchased from Dynalloy Inc., USA and tensile steel spring from the local market.

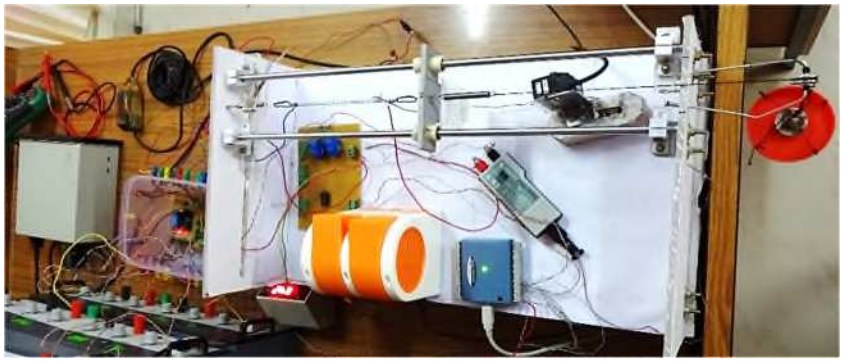

Fig. 1 Experimental setup

The schematic diagram of the circuit of Fig. 2 is used to explain the working of self-sensing of variable stiffness actuation of shape memory coil. In experimentation, different currents such as 0.8 A, 1.0 A, and 1.2 A are used to control the variable stiffness actuation of the SMA coil and their respective force, displacement, current, and various voltages are recorded. The instantaneous values of data are plotted after preprocessing to study the characteristics and modelling. The shape memory coil actuators operated in work production mode i.e., both force and displacement varying simultaneously. This mode of actuation has different applications such as circuit breaker, heat engine, robotics, and bioengineering, etc.

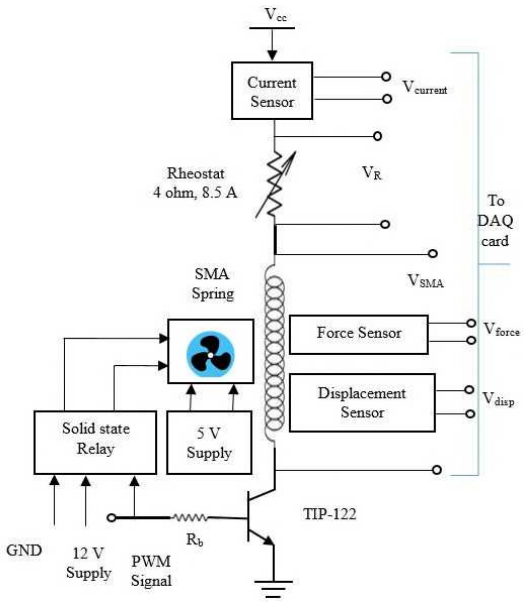

Fig. 2 Schematic diagram of the experimentation

3. Self-Sensing Stiffness of Shape memory coil

The SMA utilized earlier in self-sensing mode for displacement, force, stress and strain in various applications. In robotics and automation, the shape memory coil can be utilized /used to sense the stiffness in self-sensing mode. The ML is prevalent concept and used in all fields and equally useful for self-sensing actuation of Shape memory spring. The single ML algorithm can be useful for prediction of sensing and actuation output of shape memory coil simultaneously.

The photograph of Fig.1 is physical arrangement of components and its connection to conduct the experiment. It is used to study self-sensing of stiffness characteristics and its modeling with optimized FFNN. The self-sensing stiffness characteristics is studied under different joule heating

current, and it is explained in result section. The electrical resistance of SMA wire/coil is not only sensitive to phase transformation but also depends on compositions and heat treatment (N. Ma et al. 2004). The martensite phase transform into parent/original phase due to joule heating current and electrical resistance of SMA changes. This electrical resistance can be useful to sense the stiffness of shape memory coil.

The stiffness of shape memory coil-based structure can be measured and control by using different electrical and mechanical parameter. The resistance of shape memory wire/coil depends on length, area and resistivity of a material up to certain extent and it is proved in research work (N. Ma et al. 2004). The resistance and force of given shape memory coil of different diameter are in Table No 1. To study the stiffness concerning resistance characteristics; the electrical resistance and stiffness of shape memory coil is determined from equation (1) and equation (2)

$$R_{coil} = \frac{V_{coil}}{V_s - V_{coil}} * R \tag{1}$$

$$k_{coil} = \frac{d^4 G_{coil}}{8\, n\, D^3} \tag{2}$$

where, R_{coil} is the resistance of the shape memory coil (Ω), V_{coil} is voltage of the Shape memory coil (V), R is fixed resistance (Ω), V_S is source voltage of MOSFET (V), k_{coil} is instantaneous stiffness of the Shape memory coil (N/m), G_{coil} is instantaneous shear modulus of the Shape memory coil (N/m^2), d is wire diameter of the Shape memory coil (m) and D is coil diameter of the Shape memory coil (m). The instantaneous value of G_{coil} is changing (not fixed) and determined from stress and strain of shape memory coil.

Table 1: General Properties of SMA [10]

Wire diameter (µm)	100	125	200
Linear Resistance (Ω/m)	126	75	29
Maximum allowable force (N)	4.601	7.220	18.247
Nominal force (N)	0.275	0.422	1.079

The aim of this modeling is to predict the stiffness accurately during variable stiffness actuation and studied the stiffness of shape memory coil under different joule heating current. With the help of experimental data, the machine learning based Classical Polynomial and Feedforward Neural Network model developed. The models are trained for the instantaneous data values

recorded for 0.8 A and 1.0 A joule heating current and validated for instantaneous data values to 1.0 A joule heating current.

a. Self-Sensing Stiffness by Classical Polynomial Model.

The self-sensing of Shape memory wire/coil actuator characteristics are developed in between the contracted length/ position / strain /force/stress/temperature and electrical resistance by using approximated mathematical model with lot of assumption. But it needs to develop accurate appropriate and reliable stiffness /compliant of shape memory wire/coil model.

A classical polynomial regression technique used to find out the appropriate mathematical model that expresses the relationship between dependent variable (stiffness) and independent variable (resistance). This mathematical model describes the self-sensing characteristics and is function of the independent variable involving one or more coefficients.

The model structure of nonparametric model (Classical Polynomial Regression Model) is different from parametric model, and it is not specified earlier but determined directly from given training data set. It cannot be said that the nonparametric model does not have a parameter, but the number and nature are flexible and depend on training data set.

The two stochastic stationary ergodic variables of shape memory coil {resistance} and {stiffness} given as input and output data values.

$$x_i \in R_{sma} \subset \mathbb{R}$$

where R_{sma} is compact form of representation and resistance of shape memory coil.

$$y_i \in k_{sma} \subset \mathbb{R}$$

where k_{sma} is compact form of representation and stiffness of shape memory coil.

Further it is assumed that the input and output data recorded from experimentation to unknown function, and it is the result from the experimental observed data

$$f\colon R_{sma} \rightarrow \mathbb{R}$$

$$y_i = f(x_i) + e_i \qquad 3$$

where, i =1, 2, 3, 4, ….., n and

$e_i \in \mathbb{R}$, e_i is error and classical polynomial of degree p will approximate the function f with fitting error $\hat{e}_i$

$$f(x_i) = \gamma_p(x_i, w) + \hat{e}_i \qquad 4$$

where i =1, 2, 3, 4, ….., n and $\gamma_p(x_i, w)$ is polynomial of order p and $x_i \in R_{sma}$. The vector $w \in \mathbb{R}^{N^{pol}(N)}$ finds the values of coefficients of polynomial function γ_p

where $N^{pol}(p) = \sum_{l=0}^{p} \binom{d+l-1}{l}$, where d is fixed $N^{pol}(p)$ is increasing function of p and it represent the complexity of $\gamma_p(x_i, w)$

3.1 Self-Sensing Stiffness Actuation by Feedforward Neural Network (FFNN):

Machine Learning is a parallel path to an analytical model. The various Machine learning algorithms are used to implement the sensing, actuation, and control problems. It produced a promising result in the last few years. These Machine learning methods involve the empirical approximation of an unknown model of Sensor behavior e.g., sensing of force or system dynamics such as the linear or rotary motion of the manipulator. So, Feedforward Neural Network is considered for the ML algorithm (Keene Chin et al.2020). Artificial Neural Networks are the most widely used ML algorithm to solve the categorical and regression problem of prediction online and offline.

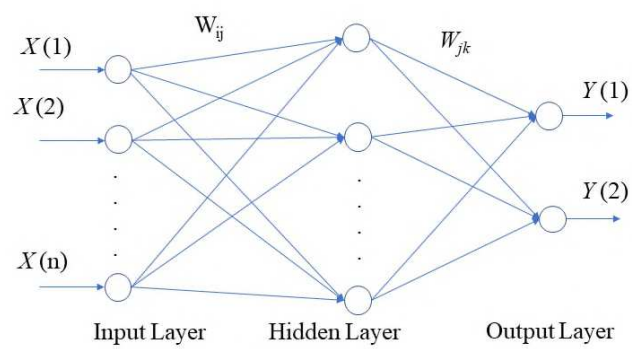

Fig. 3 Architecture of Feedforward Neural Network

It has the number of neurons interconnected according to an algorithm to process and predict the information. The neurons interact with each other by weighted connection. These neurons are arranged in three different layers e.g., input layer, the hidden layer, and the output layer. Generally, the input layer and output layer are one in number. The hidden layer may be in more than one. The input layer receives the input data or information, output layer holds the output or response. The hidden layer determines the complicated association between the neurons. Here supervisory technique is used to train the FFNN, and its architecture is in Fig.3.

It is assumed that the input layer has n inputs neurons i.e. i is varying from 1,2, 3,…n, and the hidden layer have q neurons i.e. j is varying from 1,2, 3,…q. The connections weight values are represented by Wij, where i and j are varying, and connections weight between hidden layer and output layer represented by Wjk where j and k are varying and integer values.

The input to and output from hidden layer neurons are represented by A_j and B_j. The mathematical formulation of FFNN is.

$$A_j = \sum_{i=1}^{n} \left(W_{ij} X(i)\right) \tag{5}$$

$$B_j = f\left[A_j\right] = f\left[\sum_{i=1}^{n} \left(W_{ij} X(i)\right)\right] \tag{6}$$

$$C_k = \sum_{j=1}^{q} \left(W_{jk} B(j)\right) \tag{7}$$

$$Y_k = f[C_k] = f\left[\sum_{n=1}^{q} \left(W_{jk} B(j)\right)\right] \tag{8}$$

where, $f()$ is activation function to calculate output of each neuron.

3.2 Bayesian Optimizations for FFNN Model

The Machine Learning algorithm can be optimized by various methods such as Manual, Grid Search, Random Search, and Bayesian search etc. Bayesian search optimization is a good choice and state of art global optimization technique. Here Bayesian optimization is used to optimize the value of the Learning rate and the number of hidden neurons. It builds a probability model of the objective function to propose a smarter choice for the next set of hyperparameters to evaluate. It is more efficient at finding the best hyperparameter for a machine learning model than random or grid search. So that given FFNN algorithm gives the best performance and is measured on testing data set. It is a tradeoff between exploitation and explorations of the evaluation function of some criteria such as accuracy. It builds the probability model of the objective function and uses it to select the most promising hyperparameters to evaluate in the true objective function. Bayesian optimization represents a powerful tool in helping experts to optimize their machine learning models. Selecting the best Bayesian optimization technique for each problem of interest is often non-intuitive.

3.3 Comparison Criteria of Model

The Classical Polynomial Regression and Feedforward Neural Network performance are compared based on standard deviations (SD), Root means square error (RMSE), the goodness of fit (R^2), and the fraction of variance unexplained (FVU). The standard deviation gives the information about the range of error that model response deviates from the mean average value of observed data. The smaller the value of SD better is the model prediction. The RMSE is the standard deviation of residuals, and it measures how much is distance between observed response and predicted response, the closer the distance more the accurate the model. The goodness of fit (R^2) can explain how much of the predicted characteristics are accurate. If R^2 (goodness of fit) = 95 % means our model can predict at an accuracy of 95 %. Here higher the values of R^2, the better is the model. The FVU means the variation in observed values is remains unexplained by the model. The smaller the value of FVU better is the performance of the model.

4. Experimental and Simulation Result of Modelling

The measurement data collected at the sampling rate of 7 due to the low-frequency bandwidth of SMA materials. There were two methods of machine learning-based modelling of self-sensing variable stiffness actuation results presented and discussed. We found that the Feedforward Neural Network-based model perform better. First the optimizations of an order of classical polynomial and optimization of hyperparameter of Feedforward Neural Network model done.

a. Data Cleaning/Preprocessing

Machine learning means learning from the data. To give the best performance on unseen similar kinds of data, the model must learn from given data. This is decided by how the model learns accurately during a training phase. Before starting the training phase, the raw data is obtained from real-world information and may contain a lot of noise and outliers. Also, the data collected might not be homogeneous, which means the values of different features might belong to different ranges. The various types of smoothing functions used to remove the outliers/noise. After removal of outliers /noise, the data scaled/normalized to make it homogeneous.

$$X_{\mathrm{i}} = \frac{x_{\mathrm{i}} - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

$$x_{\mathrm{i}} = X_{\mathrm{i}}(\mathrm{x}_{\max} - x_{\min}) + x_{\min} \tag{10}$$

where, X_{i} is normalized data values, x_{i} is denormalized data values, $x_{\max}$ is the maximum value in a given data set and $x_{\min}$ is the minimum value in given data set.

4.1 Optimization of Classical Polynomial Model

Fig. 4 shows the algorithm-based procedure to find the correct order of the polynomial model in comparison with the experimental sensor's characteristics; it can be seen that the sixth order polynomial model is the optimum match with the experimental data because of minimum root mean square error (RSME) value. So, the minimum value of RMSE of 6th order polynomial model is 0.0067.

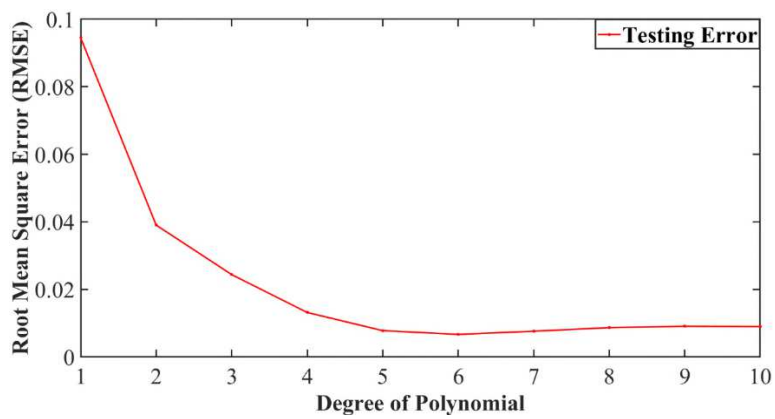

Fig. 4 Optimization of an order of Polynomial Regression

After pre-processing the collected data from experimentation, the data is split into training and validation. The model is trained by using algorithm/MATLAB code and learn the nature of supplied data. After training, the trained model is validated for unseen data. Now during training and validation of the first method (Classical Polynomial) of modelling, the absolute value of error was recorded and presented in Fig. 5. During training, an error was a lesser and a little bit higher during testing because known data were used for training and unknown data for testing. The maximum value of absolute error during training was less than 0.03 and during testing 0.17. The difference between an absolute error of training and testing data is 0.14.

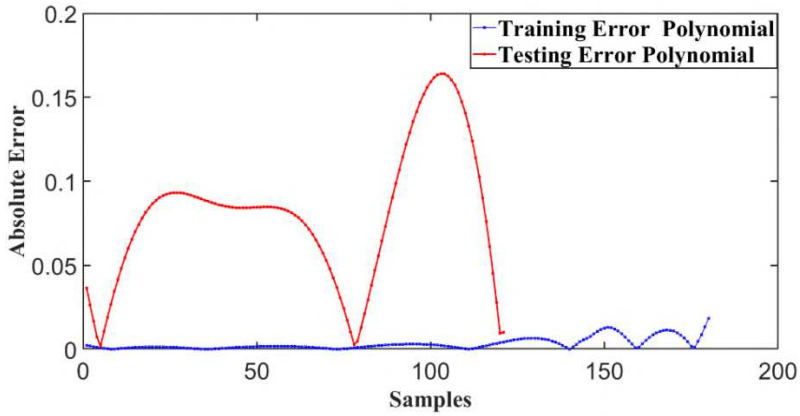

Fig. 5. Error during Training and Testing of Polynomial Regression Model

The classical polynomial model is implemented in MATLAB 2020b software by writing code using "polyfit" and "polyval" functions. This model considers the data during the austenite phase and conclusion of implementation is the relation between stiffness and resistance by Eq. (11).

$$k = 9.4538 * R_{SMA}^{6} - 40.2965 * R_{SMA}^{5} + 67.9703 * R_{SMA}^{4} - 57.3721 * R_{SMA}^{3} + 26.0591 * R_{SMA}^{2} - 6.7963 * R_{SMA} + 1.0185 \quad (11)$$

where, k is the stiffness in N/m and R_{SMA} is the resistance in ohm of shape memory coil actuator.

4.2 Tuning of Hyperparameters of FFNN

The processed data after recorded from experimentation in which the resistance change of Shape memory coil is used as features (input data values) and Stiffness change of coil are used as labels (output data values). To find the best hyper parameter from given range of values for given data set; the Bayesian search algorithm runs a model many times and uses past model to build the new model. This is the main idea of Bayesian search to achieve most accurate model within less time. The Bayesian algorithm makes a model of an objective function, and this model assumes that observations can contain noise. So, the best observed feasible point is the one with the lowest returned value from objective function evaluations. The best estimated feasible point is the one that has the lowest estimated mean value according to the latest model of the objective function.

Learning Rate: In machine learning, it is tunning parameter to streamline the algorithm which decides the progression size at every emphasis. It figuratively decides the speed at which ML model learn. When training is started with large learning rate, the loss function does not improve initially but as learning rate reduces the loss function start decreasing within few iterations. To find the best learning rate is challenging and tedious time consuming. To generate final optimal

set of weight for trained Network, the learning rate should be small, but it will take long time to train.

Hidden Layer size (Neurons): Basically, one hidden layer is enough to solve the majority of the problems. If the data are linearly separable, with fewer dimensions or features, and large dimensions or features, then no hidden layer, one hidden layer, and more than one hidden layer may require respectively. Once the hidden layer is fixed, then hidden neurons are decided. The different ways, we can find the number of Neurons in the hidden layer through the various search methods. So, Bayesian search is one of the methods to determine neurons in the hidden layer.

Bayesian search optimization find the global minimum with less time compared with other existing methods (Grid and Random search) by providing elegant framework. It keeps track of past evaluation results which they use to form a probabilistic model mapping hyperparameters to a probability of score on objective functions. This model is called a "Surrogate" for a objective function. The "Surrogate" is much easier to optimize than the objective function and Bayesian methods work by finding the next set of hyper parameters to evaluate on the actual objective function. The detailed results of the Bayesian search optimization technique on observed objective functions and estimated function are

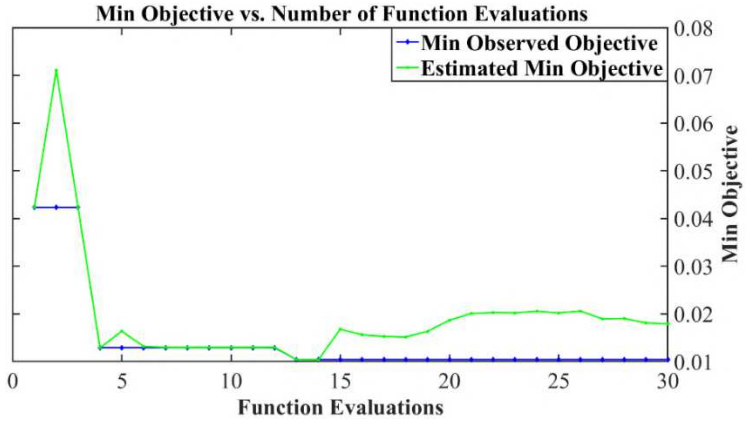

Fig. 6 Optimization of Functions

Total function evaluations: 30
Total elapsed time: 97.5065 seconds
Total objective function evaluation time: 68.7804
Best observed feasible point:
Hidden Layer Size = 7
Learning rate = 0.14157
Observed objective function value = 0.01041

Estimated objective function value = 0.027402
Function evaluation time = 3.1389

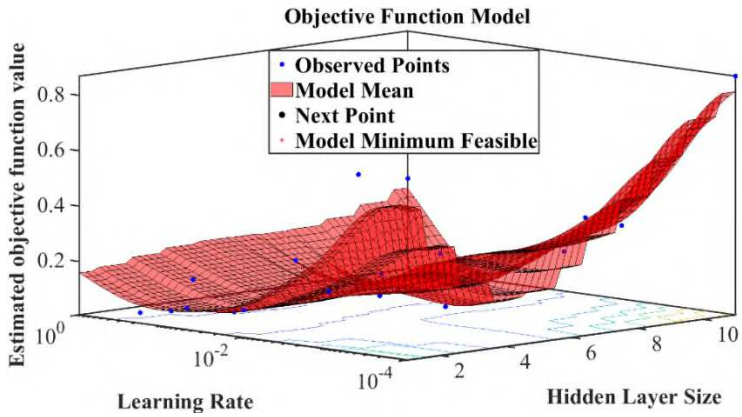

Fig. 7 Tuning of Hyperparameter of Feedforward Neural Network

Best estimated feasible point (according to models):
Hidden Layer Size = 8 learning rate = 0.093858
Estimated objective function value = 0.017894
Estimated function evaluation time = 1.9749

The training and testing of absolute error of Feedforward Neural Network is in Fig. 8. The difference between them is small. After optimization of hyperparameter of FFNN, the learning rate and the number of hidden layer neurons are used $\eta = 0.093858$ and 8 for updating the weights of FFNN.

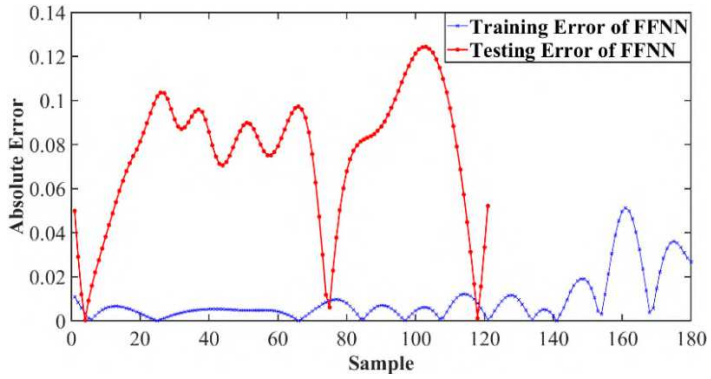

Fig.8 Error during Training and Testing of Feedforward Neural Network

4.3 Performance evaluation of FFNN

The training of FFNN model done by using three different sets of instantaneous values of various voltages of Shape memory coil subjected to the Joule heating current of 0.8 A, 1.0 A 1.2 A with the excitation frequency of 10 Hz. All these three sets of various voltages are converted

into resistance change and stiffness change. These three sets of resistance and stiffness values of data are converted into training, validation, and test set. The results of training and learning are shown in Fig. 9. It is found that FFNN is trained well and there was no underfitting and overfitting occurred during training, validation, and testing of neural network.

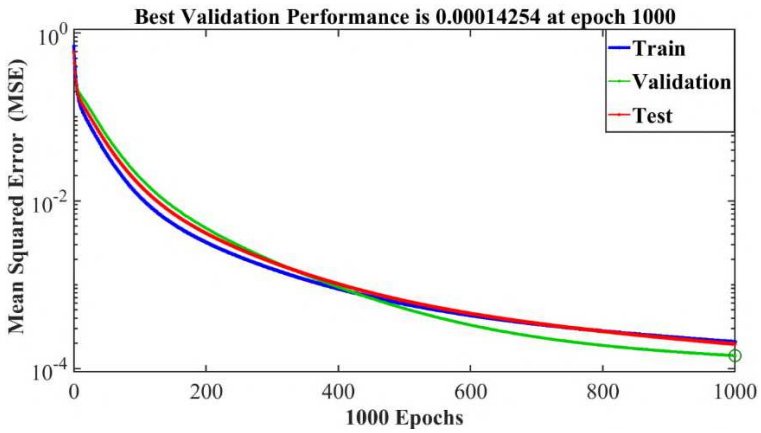

Fig. 9 Performance of Feedforward Neural Network

Error Histogram: This histogram indicates how the predicted values are different from target values. It measures the difference between FFNN predicts and experimental data. It showed the distribution of errors from FFNN on training, validation, and testing time in Fig.10.

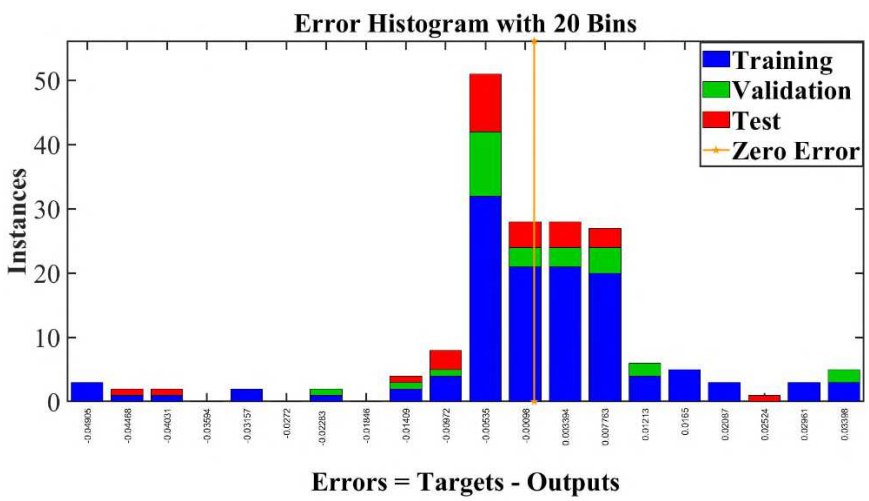

Fig.10 Error Histogram of FFNN

It is the most standard method to test the performance of a model. Here the regression analysis of FFNN at four different durations such as training, validation, testing, and all in Fig. 11.

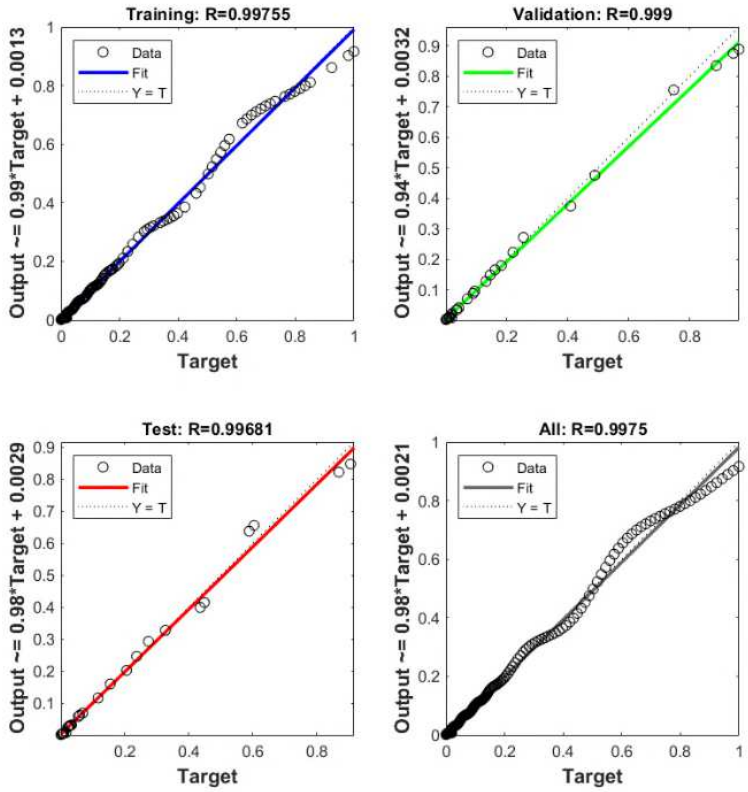

Fig.11 Linear Regression Analysis of FFNN

This analysis gives three parameters of output variables (stiffness). One is y-intercepts, the second is a slope, third is the correlation coefficient between scaled output and target.

Table 2 Linear Regression Analysis of FFNN

Parameter \ Duration	Training	Validation	Test	All
Y-intercept	0.0013	0.0034	0.0032	0.0019
Slope of Curve	0.9900	0.9700	1.0000	0.9900
Correlation Coefficient	0.99822	0.99917	0.99854	0.99834

To understand the performance of FFNN on various testing metrics, if it is found correct then the model can be deployed for applications. To check the accuracy of prediction of the FFNN model, the linear regression results play an important role and gave three parameters.

1) Y-intercept of curve
2) Slope of curve
3) The correlation coefficient between scaled output and target

If the slope would be 1, y-intercept would be zero, and the correlation coefficient would be 1, then there would be a perfect prediction of the model. If the correlation coefficient is 0.99822, then its accuracy of prediction is 99.822 %. Here the Table No.2 gave the result of the FFNN model.

4.4 Comparison of Results

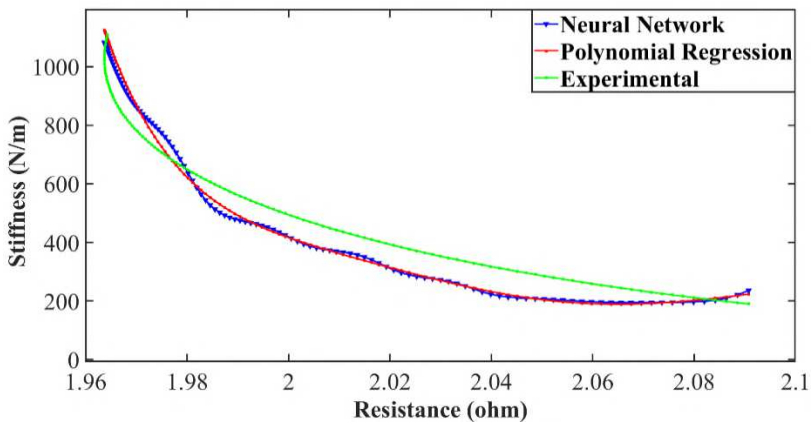

Fig.12 Comparison of FFNN, Polynomial and experiment results

The two methods of modeling used to model the experimental result of self-sensing of variable stiffness actuation of Shape memory coil. The first two sets of data are used to train the FFNN and the third data set is used to validate the FFNN model which is unseen data of resistance to predict the stiffness of the SMA coil. The FFNN model with hyperparameter decided by Bayesian search was used to train the network and resultant validation response of it along with polynomial model and experimental is in Fig.12 The standard deviation, root mean square error value, goodness of fit and fraction variance unexplained value is basis to compare the performance of two machine learning methods and is in Table 3.

Table 3 Comparison of Performance of Models

Parameter \ Method	Classical Polynomial Regression	Feedforward Neural Network
Standard Deviations (SD)	0.0901	0.0817
Root Means Square Error (RMSE)	0.0898	0.0840
The goodness of Fit (R^2)	90.5844	95.2650
Fraction Variance unexplained (FVU)	0.0942	0.0825

The range of values of stiffness and resistance of shape memory coil found in Table 4. The stiffness response for different joule heating currents found that it increases with an increase in current and decrease in shape memory coil resistance. The maximum value of stiffness of shape memory coil stiffness found 62.8684 N/m, 156.2679 N/m, and 2130.4059 N/m for Joule heating current of 0.8 A, 1.0 A, and 1.2 A respectively. At the same time, the maximum value of the shape memory coil resistance of variable stiffness actuator was 2.5461 Ω, 2.2530 Ω, and 2.0446 Ω.

Table 4 Resistance and Stiffness Values of Shape Memory Coil [10]

Current (A) \ Property	Resistance of SMA coil (ohm)		Stiffness of SMA coil (N/m)	
	Minimum	Maximum	Minimum	Maximum
0.8	2.4426	2.5461	21.7310	62.8684
1.0	2.1310	2.2530	21.7521	156.2679
1.2	1.9454	2.0446	23.4013	2130.4059

5 CONCLUSION

The stiffness of the shape memory coil is linearly dependent upon the current and electrical resistance. The stiffness of the SMA coil is directly related to current and inversely related to electrical resistance. The Bayesian search method provides optimized values for hyperparameter by evaluating 30 functions and surpasses human expertise. Then optimized hybrid FFNN model is used to train the experimental data to predict the stiffness of Shape memory coil. The self-sensing ML based FFNN model is a promising technique since it has more than 95.2650 %

accuracy to predict the stiffness. The improved results of the hybrid FFNN model for prediction of stiffness obtained from the classical polynomial model by integrating Bayesian search in hybrid FFNN and it found that FFNN model as a soft sensor performs better than classical polynomial model. The proposed FFNN based soft sensor model eliminates the force and displacement sensors to sense the stiffness of shape memory coil of variable stiffness actuator. It saves the cost of the additional sensors and simply the overall process of ascertaining the stiffness of the shape memory coil. The variable stiffness actuation with sensing power can be applied in diverse defence-oriented services such as robotics, device automation, aeronautics, and structural health monitoring.

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Availability of data and material: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Code availability: The Code that support the findings of this study are available from the corresponding author upon reasonable request.

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