Machine learning-based self-sensing of 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 in smart equipment as well as robotics. The stiffness characteristic of the shape memory coil (SMC) is sensed during actuation which plays a significant role in development of intelligent robotics in defense systems. The electrical property of SMC 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 of the equipment. 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 SMC during actuation accurately. Therefore, a soft model based on machine learning is proposed in this paper for autosensing of the stiffness in SMC. 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 SMC is a cumbersome task. Hence, we have proposed an automated method to predict the stiffness of the SMC using soft computing-based methods. The Classical Polynomial and Bayesian optimization-based Feedforward Neural Network (FFNN) models are developed for analyzing the stiffness of the SMC. It is found that the hybrid 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.

Keywords Shape memory coil · Joule heating · Stiffness · Self-sensing actuation · Defense applications, Equipment · Machine Learning

1 Introduction
In an intelligent Robotics, defense devices and bio-engineering system, an active structure is needed that can change their mechanical characteristics and transfer their action to the passive structure (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 and Dhanalakshmi 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 Machine Learning (ML) (Cebollada et al. 2021; Hiraga and Ohkura 2021; Senapati et al. 2021) 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 Feedforward Neural Network (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 (Machine Learning-based Feed-Forward Neural Network) developed with a finite set of experimental data. To decide the external parameters (hyper-parameters) such as learning rate and number of hidden layer neurons is a difficult task and can be solved by Bayesian search. The Bayesian search is the optimization technique of Machine Learning (ML) (Bachiller et al. 2021) that can find the optimum hyper-parameters (learning rate and number of hidden layer neurons) of Feed-forward Neural Network (FFNN). So self-sensing of Shape memory coil by ML can be the suitable alternative to the mentioned problem (Kaur and Kadam 2021).

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 (SMA) 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 (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 (Hu et al. 2021). This change in Electrical resistance property leads to development of shape memory coil (SMC) 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 objects (Awan et al. 2016; Gurang and Banerjee 2016). The electrical resistance is changing nonlinearly with contraction of length of SMA wire. So, it is suggested that Neural Network handles nonlinearity better and is used to model the relation between resistance and contracted length of SMA wire (Awan et al. 2016). 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 (Gurang and Banerjee 2016). The self-sensing of strain of SMA wire by Polynomial Model 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 characteristic is independent of bias spring stiffness and environmental temperature (Wang et al. 2012). To characterize the self-sensing of position of SMA wire, Neural Network method is better than first-order equation and is 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 become compact (Estibalitz et al. 2010).

The Artificial Neural Network model is developed to map the self-sensing of rotary position of manipulator and electrical resistance of SMA wire. The Self-Sensing ANN model predicts the rotary position accurately up to minimum of 0.8°. The proposed self-sensing model is robust with respect to environmental temperature variations from — 5 to 45 °C. The performance of model is sensitive to pre-stress and load on manipulator (Narayanan and Mohammad 2016).

The innovative way to find the electrical resistance of SMA wire for self-sensing of wire position is proposed in Kaur and Kadam (2019). 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 (Kaur and Kadam 2019). 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 suggests that creation of compact self-sensing actuator is viable (Yasuyuki and Kagawa 2019). The shape memory spring is used as a sensor for displacement and stiffness which is mathematically obtained by linear equation. It 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 (Miao lei et al. 2017).

The stiffness of SMA spring is controlled 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 (Hu et al. 2021). The
self-sensing modeling and investigations of stiffness characteristics of SMA spring are analyzed. 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 and Dhanalakshmi 2018).

The modified new mathematical function relating the stiffness and temperature of SMA spring and hysteresis characteristics between them can be controlled by electrical parameters such as current, frequency and pre-stress. The mathematical function of stiffness is verified with experimental data (Bhagoji and Dhanalakshmi 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 (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 (Jiang et al. 2021). 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 (Alessandri et al. 2009). The Neural Network universal approximator which is performing better than polynomial regression explained correctly in Szemenyei and Estivill-Castro (2021). The progress report of how Machine learning is useful to such a system whose mathematical/analytical function is not known exactly is reported by Rahmani et al. (2021).

The focus of Narayanan and Mohammad (2016) is on Neural network-based self-sensing to position/contracted length/displacement of SMA coil modeling but not on the optimization of the model. The self-sensing of the displacement force of SMA wire is done by conventional way of modeling (Yasuyuki and Kagawa 2019). The different curve fitting equations are used to model the sensor characteristics and determine the best out of it for calibration in Jiang et al. (2021). Any mathematical function can be modeled by universal approximator (FFNN) and it is called white box modeling in Alessandri et al. (2009). 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 Chin et al. (2020). This paper could achieve maximum 88.76% accuracy by Random Forest algorithm of Machine Learning to predict Diabetes Mellitus (Cebollada et al. 2021). In this paper, Logistic regression and Multinomial Naïve Bayes algorithm are used to predict CORONA Virus infection (Hiraga and Ohkura 2021). In this research work, COVID-19 cases prediction is done by using piecewise regression (Senapati et al. February 2021). The Random Forest and Support Vector Machine (SVM) algorithm are used to classify the susceptibility score of Individual toward COVID-19 infection (Bachiller et al. 2021).

Auto-sensitive actuation (SSA) helps to detect 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. If we use ordinary static or deterministic methods then they can perform well if the sensing data is of same pattern but in order to meet the needs of dynamic changes, there is a need for machine learning approaches. The machine learning approaches can learn from offline as well as online data and can perform better even if the data arrives in a dynamic environment. Therefore, we have chosen machine learning methods and test them on our problem statement.

In an intelligent robotics, defense devices and bio-engineering system, an active structure is needed that can change their mechanical characteristics and transfer their action to the passive structure. 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 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. Hence, we are proposing machine learning-based approach for self-sensing of the stiffness of shape memory coil actuator assist in military equipment where robotics play a vital role.

1.2 Research gaps

None of the research work is aimed to study the relationship between electrical resistance and stiffness of shape memory alloy (SMA) Coil actuator by Machine Learning-based Hybrid Feedforward Neural Network or even machine learning approaches. Self-sensing refers to the measurement of stiffness of Shape Memory Coil during actuation of actuator by electrical property. It is used to calculate its stiffness directly, instead of using a stiffness
sensor. In our approach, electrical properties such as resistance, sensing mechanism are used to sense the stiffness of the shape memory coil. There is currently no well-established analytical model that can accurately predict the stiffness of sensing during actuation by electrical resistance. As a result, in this paper, a data-driven intelligent model based on Machine Learning (ML) is proposed for stiffness auto-sensing as this research is useful in robotics in sensor-based automated equipment in defense systems.

1.3 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.

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

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

The description of the work is started with an introduction, background, and a review of referred papers relating to stiffness, self-sensing, and modeling of the Shape-memory coil actuator. Section 2 explains the hardware components, experimentation, circuit operations, and experimentation details. Section 3 explains information about the methodology of the classical Polynomial model and FFNN with its optimization by Bayesian search. Section 4 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 provides a summary of the proposed FFNN hybrid approach.

2 Proposed work

2.1 Experimentation and circuit operation

The data-driven model needs enough experimental data to model the characteristics between stiffness and resistance of shape memory spring. The experimental facility and conduction of experimentation are mandatory for the research study. The proposed experimental setup consists of an actuation system, Joule heating circuit, power supply system, and data acquisition system with its arrangement as shown in 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 the transistor on–off, one 40-W rheostat to find the accurate resistance of the SMA coil and the required power supply. The D.C. regulated power supply, dual power, and A.C. power supply are required 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 of the signals are directed directly to the data acquisition card which allows the recording of data acquisition system into the computer memory.

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, 1.0, and 1.2 A are used to control the variable stiffness actuation of the SMA coil and their respective forces, displacements, currents, and voltages. The instant values of data are plotted after preprocessing of the collected values to study the characteristics of the system.

When the shape memory coil of actuators operates in work production mode then both force and displacement can vary simultaneously. This mode of actuation has different applications such as circuit breaker, heat engine, robotics, and bioengineering.

2.2 Self-sensing stiffness of shape memory Coil (SMC)

In robotics and automation, the SMC can be utilized to sense the stiffness in self-sensing mode. The Machine learning-based approach is a prevailing concept and its usage is explored in this research work for sensing the actuation of shape memory coil. The single ML algorithm can be used for prediction of actuation output of SMC in robotics and aligned fields. Figure 1 depicts the physical arrangement of components to conduct the experimental study. It is used to study self-sensing of stiffness characteristics and its modeling with optimized FFNN. The self-sensing stiffness characteristics are studied under different Joule heating currents, and the outcome is explained in the
The electrical resistance of SMA wire/coil is not only sensitive to phase transformation but also influenced by the compositions of materials and heat treatments. There are two phases in SMA, i.e., Austenite and Martensite phases. The Martensite phase can be transformed into parent/original phase due to Joule heating and electrical resistance of SMA. This electrical resistance is useful to sense the stiffness of shape memory coil. The stiffness of shape memory coil-based structure can be measured and controlled by using different electrical and mechanical parameters. The resistance of SMC is impacted from the length, area and resistivity of a material up to a
certain extent and it is proven in the proposed research. The resistance and force of given SMC of different diameters are shown in Table 1. To study the stiffness-related resistance characteristics, the electrical resistance and stiffness of shape memory coil are derived from Eq. (1) and Eq. (2).

\[
R_{\text{coil}} = \frac{V_{\text{coil}}}{V_s - V_{\text{coil}}} \quad (1)
\]

\[
k_{\text{coil}} = \frac{d^4 G_{\text{coil}}}{8nD^3} \quad (2)
\]

where \(R_{\text{coil}}\) is the RSMA-resistance of the shape memory coil (\(\Omega\)), \(V_{\text{coil}}\) is VSMA-voltage of the Shape memory coil (V), \(R\) is fixed resistance (\(\Omega\)), \(V_s\) is source voltage of MOSFET (V), \(K_{\text{coil}}\) \(k\) represents the instantaneous stiffness of the Shape memory coil (N/m), \(G_{\text{coil}}\) is instantaneous shear modulus of the SMC (N/m²), \(d\) is wire diameter of the Shape memory coil (m) and \(D\) is coil diameter of the SMC (m). The instantaneous value of \(G_{\text{coil}}\) is varying and can be determined from stress and strain of shape memory coil (SMC).

The aim of this modeling is to predict the stiffness accurately during variable stiffness actuation. This research studies the stiffness of shape memory coil under different Joule heating currents. With the help of experimental data, the machine learning-based Classical Polynomial (CP) and Feedforward Neural Network (FFNN) models are designed. The models are trained for the instantaneous data values recorded for 0.8 and 1.0 A Joule heating currents and validated for instantaneous data values up to 1.2 A Joule heating current.

### 3 Self-sensing stiffness by machine learning model

#### 3.1 Classical polynomial model for self-sensing stiffness

The self-sensing of shape memory coil actuator characteristics are developed with respect to the length, position, strain, force, temperature and electrical resistance by using approximated mathematical model with the underlying assumptions. An attempt is made to develop an accurate, appropriate and reliable stiffness of shape memory coil model.

A classical polynomial regression technique is 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 function of the independent variable involving one or more coefficients.

The model structure of nonparametric model (CP Regression Model) is different from parametric model, and it is not specified earlier but has been determined directly from the given training dataset. It cannot be claimed that the nonparametric model does not have any parameter, but the nature of the model is flexible and dependent on the training dataset.

The two stochastic stationary ergodic variables of SMC, \{resistance\} and \{stiffness\}, are given as input and output data values.

\[
x_i \in R_{\text{sma}} \subset \mathbb{R} \quad (3)
\]

where in Eq. (3), \(R_{\text{sma}}\) is compact form of representation and shows resistance of SMC.

\[
y_i \in k_{\text{sma}} \subset \mathbb{R} \quad (4)
\]

where in Eq. (4), \(k_{\text{sma}}\) 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 the unknown function, and the obtained result from the experimental study is described by Eq. (4)

\[
f : R_{\text{sma}} \rightarrow \mathbb{R} \quad (5)
\]

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 \(\tilde{e}_i\) as shown in Eq. (5)

\[
f(x_i) = \gamma_p(x_i, w) + \tilde{e}_i \quad (6)
\]

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

Where \(N_{\text{pol}}(p) = \sum_{l=0}^{p} \binom{d+l-1}{l}\), where \(d\) is fixed \(N_{\text{pol}}(p)\) is increasing function of \(p\) and it represents the complexity of \(\gamma_p(x_i, w)\).

Finally, by employing the above-mentioned method, the stiffness of the memory coil of actuator is obtained in terms of Nm⁻¹ (Newton (N) per meter).

| Table 1 General Properties of SMA (Awan et al. 2016) |
|-----------------|--------|--------|--------|
| Wire diameter (\(\mu\)m) | 100    | 125    | 200    |
| Linear resistance (\(\Omega\)m) | 126    | 75     | 29     |
| Maximum allowable force (N) | 4.601  | 7.220  | 18.247 |
| Nominal force (N) | 0.275  | 0.422  | 1.079  |
3.2 Self-sensing stiffness actuation by feedforward neural network (FFNN)

ML is a parallel path to an analytical model and it is important to explore the usage of ML or deep learning-based techniques for self-sensing of the stiffness in actuators. The various ML algorithms are used to implement the sensing, actuation, and control problems. It is producing promising results. 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, FFNN is considered for designing the model (Chin et al. 2020). Artificial Neural Networks are the most widely used machine learning-based algorithms to solve the categorical and regression problem of prediction for online and offline data models.

It has number of neurons which are interconnected to process the information for deriving the output. The neurons interact with each other by weighted connections. These neurons are arranged in three different layers e.g., an input layer, hidden layer, and an output layer. Generally, the input layer and output layer are one in number. The hidden layers can be more than one and the hidden layers can be defined as per the problem statement. 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 and ‘i’ is varying from 1, 2, 3,...n. The hidden layers have ‘q’ neurons and ‘j’ is varying from 1, 2, 3,...q. The connections weight values are represented by $W_{ij}$, where ‘i’ and ‘j’ are varying and connection weight between hidden layer and output layer is represented by $W_{jk}$, where ‘j’ and ‘k’ are varying integer values.

The input to and output from hidden layer neurons are represented by $A_i$ and $B_i$. The mathematical formulation of FFNN is in Eq. (7) to (10).

$$A_i = \sum_{i=1}^{n} (W_{ij}X(i)) \quad (7)$$

$$B_i = f[A_i] = f \left[ \sum_{i=1}^{n} (W_{ij}X(i)) \right] \quad (8)$$

$$C_k = \sum_{j=1}^{q} (W_{jk}B(j)) \quad (9)$$

$$Y_k = f[C_k] = f \left[ \sum_{n=1}^{q} (W_{jk}B(j)) \right] \quad (10)$$

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

3.3 Bayesian optimizations for FFNN model

The learning algorithms can be optimized by various methods such as manual methods, grid Search, random Search, and Bayesian search. Bayesian search optimization is considered as a global optimization technique which can be applied to obtain the optimal results. In our problem statement, Bayesian optimization is used to optimize the value of the learning rate and to define the number of hidden neurons to propose the stable model. It forms a probabilistic model of the objective function to suggest a smarter choice for the next set of hyper-parameters to evaluate the FFNN model. It is an efficient method to determine the best hyper-parameters for deep learning model as compared to random search or grid search. The self-sensing stiffness of shape memory coil is measured by the deep learning-based approach FFNN, and Bayesian technique is used to determine the layered structure of the feed-forward neural networks. If we have to train FFNN manually then it takes so many months to train the neural networks to obtain the accurate results. But, by using the Bayesian method, it is an optimal way to determine the structure of the FFNN as it helps to decide the layered structure of the FFNN. Hence, these two methods are complementary to each other. Therefore, the proposed FFNN algorithm gives the optimal performance while applied on the problem statement of self-sensing of SMC in defense-based equipment. The model is evaluated on the dataset. It represents the tradeoff between exploitation and explorations of the evaluation function which attempts to design the optimal forecasting model for accurate predictions. It builds the probability model of the objective function to select the most promising hyper-parameters to build the accurate forecasting model. Bayesian optimization represents itself as a powerful tool to design the FFNN-based prediction model by deciding the optimal architecture with input, output and processing hidden layers.
4 Results and discussions

4.1 Performance evaluation criteria

The CP Regression and Bayesian-based FFNN ML-based models are evaluated to compare their performance with respect to standard deviations (SD), Root-mean-square error (RMSE), the goodness of fit R-squared ($R^2$) statistical parameters, and the fraction of variance unexplained (FVU). The standard deviation gives the information about the range of error where the model response deviates from the mean average value of the observed data. The smaller the value of SD, the better is the model prediction. The RMSE is the standard deviation of residuals, and it measures the distance between observed response and the predicted response. The minimal distance depicts that the predictive model is more accurate. The $R^2$ (goodness of fit) values explain the accuracy of the predicted values. If $R^2$ (goodness of fit) is 95% then our model can predict at an accuracy of 95%. The FVU specifies that the variation in the observed values remains unexplained by the model. The smaller the value of FVU, the better will be the performance of the predictive model.

4.2 Data cleaning/preprocessing

ML means learning from the data. To give the best performance on unseen similar kinds of data, the model must learn from the available data. The model learns accurately during a training phase if balanced data is supplied to the ML-based model. Before starting the training phase, the raw data is obtained from the empirical experimentation. It contains a lot of noise and outliers initially. The data collected is not homogeneous, which means the values of different features might belong to diverse ranges. In order to clean the data noise free and to process the data for ML-based model, various types of smoothing functions have been used to remove the outliers/noise from the raw data. After removal of outliers/noise, the data is scaled up or normalized to make it homogeneous as specified in Eqs. (11) and (12).

$$X_i = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$  \hspace{1cm} (11)

$$x_i = X_i(x_{\text{max}} - x_{\text{min}}) + x_{\text{min}}$$  \hspace{1cm} (12)

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

4.3 Optimization of classical polynomial model

Figure 4 shows the algorithm-based procedure to find out the correct order of the polynomial model with respect to the experimental characteristics of the sensors. It can be comprehended that the sixth-order polynomial model is the optimum match with the experimental data due to the minimum RMSE score. As it is prudent from the results that the minimum value of RMSE of 6th-order polynomial model is 0.0067 and this optimal value can be taken up for building the model.

After pre-processing of data, the data is segregated into two parts, training and testing/validation. The model is trained by using MATLAB-based simulated environment and the model learns from the nature of the supplied processed data. After training phase, the trained model is tested and validated for an unseen data. During the training and validation of the first ML-based method (Classical Polynomial), the absolute value of error is recorded and depicted in Fig. 5. The absolute error of training phase is lower than that of the testing phase. The difference is due to the variations in the known and unseen data. The testing is performed on the unseen data for ascertaining the validity of the proposed model. The maximum value of absolute error during training is achieved less than 0.03 and during testing less than 0.17. The difference between an absolute error of training and testing data is 0.14.

The CP regression model is implemented in MATLAB 2020b software by writing code using “polyfit” and “polyval” functions. This model considers the data for the Austenite mode. The conclusion of the proposed design is to exhibit the relation between stiffness and resistance as shown in Eq. (13).

$$k = 9.4538 \times \text{RSMA}^6 - 40.2965 \times \text{RSMA}^5 + 67.9703 \times \text{RSMA}^4 - 57.3721 \times \text{RSMA}^3 + 26.0591 \times \text{RSMA}^2 - 6.7963 \times \text{RSMA} + 1.0185$$  \hspace{1cm} (13)
In Eq. (13), \( k \) is the stiffness in N/m and RSMA is the resistance in ohm of shape memory coil actuator.

4.4 Tuning of hyper-parameters of FFNN

(a) The best estimated feasible point: The resistance change of shape memory coil (SMC) is used as a feature (input data values) and stiffness change of coil is used as labels (output data values). To find the best hyper-parameters from the given range of values for the given dataset, the Bayesian search algorithm runs a model many times and uses past model to build the new FFNN-based model for prediction of the accurate output. This is the main idea of Bayesian search to achieve most accurate model within lesser span of time. The Bayesian algorithm makes a model of an objective function, and this model assumes that the observations may contain noise. Therefore, the best observed feasible point is the one which contains the lowest returned value from the 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.

(b) Learning rate: In ML-based learning, the fine-tuning of parameters is streamlined with the ML-based algorithm which decides the progression size at every step to provide accurate results. It figuratively decides the speed at which ML model can learn from the given data. When training is initiated with the large learning rate, the loss function does not improve initially but as learning rate reduces, the loss function starts shrinking within a few iterations. To find the best learning rate is a challenging and cumbersome job. To generate final optimal set of weights for the trained neural network, the learning rate should be minimal.

(c) Hidden layer size (Neurons): Basically, one hidden layer is enough to solve the majority of the problems.

If the data is linearly separable, with fewer dimensions then no hidden layer or may be one hidden layer is required but if the data has larger dimensions or features then more than one hidden layer may require, respectively. Once the hidden layers are finalized, the hidden neurons can be decided. There are methods to determine the number of Neurons in the hidden layer through diversified search methods. In our work, Bayesian search is utilized to determine neurons in the hidden layer and to decide the architecture of the FFNN.

Bayesian search optimization finds the global minima with lesser span of time. It keeps track of the previously evaluated results to utilize them for forming a probabilistic model that can map the hyper-parameters to a probability of score on objective functions. This model is called a “Surrogate” for an objective function. This method assists in optimizing the layered structure of the neural network by...
finding the next set of hyper-parameters to evaluate the actual objective function for optimal output. The detailed results of the Bayesian search optimization technique on the observed objective functions and on the forecasted function are shown in Figs. 6 and 7.

The training and testing of absolute error of Bayesian optimization-based FFNN model are shown in Fig. 8. After the optimization of hyper-parameters of FFNN, the learning rate is set to 0.093858 and the number of hidden layer neurons is set to 8 and corresponding weights are also updated in FFNN model.

In Fig. 8, the error rate during training and testing of the Bayesian optimization-based FFNN is presented. The testing data also contain the unseen data; therefore the error rate for testing data is more as compared to the training data.

4.5 Performance evaluation of FFNN

The training of FFNN model is performed by using three different sets of instantaneous values of diverse voltages of SMC subjected to the Joule heating current of 0.8, 1.0 and 1.2 A with the excitation frequency of 10 Hz. All these three sets of diverse 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 no underfitting or overfitting is observed during the training, validation, and testing of neural network.

(a) Error Histogram: This histogram indicates the difference between the predicted values and the...
target values. It measures the difference between the FFNN predicted values and the experimental data values. It shows the distribution of errors on training, validation, and testing time in Fig. 10.

(b) The regression analysis: The regression analysis of FFNN for training, validation, and testing, is presented in Fig. 11a and b. The proposed FFNN-based model shows good performance and hence, it can be adapted for self-sensing of SMC in robotics and other defense-based equipment.

This analysis gives three parameters of output variables (stiffness). One is y-intercepts, the second is a slope, third is the correlation coefficient between the scaled output and the target as shown in Table 2.

To check the accuracy of prediction of the FFNN model, the linear regression results play an important role and gave three parameters, Y-intercept of curve, Slope of curve and correlation coefficient between scaled output and target. If

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**Table 2** Linear regression analysis of FFNN

| 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 |

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**Fig. 12** Comparison of FFNN, CP regression and conventional method
the slope would be 1, Y-intercept would be zero, and the correlation coefficient would be 1, then the model is considered to be an optimal forecasting model. Where the correlation coefficient is 0.99822, then its accuracy of prediction is 99.822%. Table 2 shows that the performance of Bayesian optimization-based FFNN model is promising.

4.6 Comparison of results

The two methods of ML modeling are used to predict the experimental results of self-sensing of variable stiffness actuation of SMC. The first two sets of data are used to train the FFNN and the third data set is used to validate the FFNN model on unseen data to predict the stiffness of the SMA coil. The FFNN model with hyper-parameters decided by Bayesian search is utilized to train the network and the experimental results are shown in Fig. 12. The standard deviation, RMSE value, $R^2$ and FVU values are shown in Table 3, to compare the performance of the proposed models.

It can be inferred that both the models can be applied in real-time environment to sense the stiffness of the SMC but Bayesian optimization-based FFNN model outperforms the other model.

5 Conclusion

Though the overall stiffness and resistance are nonlinear, the stiffness of the shape memory coil is linearly reliant upon the current and electrical resistance during Austenite mode. The Bayesian optimization is used to design the architecture of FFNN for preparing the accurate prediction model for self-sensing of SMC. The Bayesian search method provides optimized values for hyper-parameters by evaluating 30 functions and by eliminating the human intervention for manual designing of the FFNN model. Then, optimized hybrid FFNN model is used to train the experimental data to predict the stiffness of SMC. The self-sensing FFNN model is a promising technique for forecasting the stiffness since it has more than 95.2650% accuracy. FVU (Fraction Variance Unexplained) metric explains the prediction of the hybrid FFNN with the value of 0.0842. The improved results of the hybrid FFNN model for prediction of stiffness are obtained by integrating the Bayesian search in hybrid FFNN and it is found that the hybrid FFNN model is projected as a soft sensor performed for prediction of stiffness of SMC in defense-oriented applications such as intelligent equipment and robotics. The proposed FFNN-based soft sensor model eliminates the force and displacement of sensors to sense the stiffness of SMC and it saves the cost of the additional sensors by simplifying the overall process of ascertaining the stiffness of the shape memory coil. The variable stiffness actuation with sensing power can be applied in diverse defense-oriented applications such as robotics, device automation, aeronautics, and structural health monitoring. The significance of the research is to replace two sensors (force and displacement sensors) with one soft sensor (proposed soft model). It will be useful in the controlling robotics and other devices which require high precision in data generated by the sensors.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest involved in this research work.

References

Alessandri A, Cassetta L, Mosca R (2009) Nonparametric nonlinear regression using polynomial and neural approximators: a numerical comparison. Comput Manag Sci 6:5–24. https://doi.org/10.1007/s10287-008-0074-3

Awan AU, Park J, Kim HJ, Ryu J, Cho M (2016) Adaptive control of a shape memory alloy actuator using neural-network feedforward and RISE feedback. Int J Precis Eng Manuf 17:409–418. https://doi.org/10.1007/s12541-016-0051-7

Bachiller P, Rodriguez-Criado D, Jorvekar RR et al (2021) A graph neural network to model disruption in human-aware robot navigation. Multimed Tools Appl. https://doi.org/10.1007/s11042-021-11113-6

Bhagoji BS, Dhanalakshmi K. (2018) Self-sensing characteristics and analysis of the stiffness of the SMA spring actuator. In: 8th IEEE
India international conference on power electronics (IICPE),
https://doi.org/10.1109/IICPE.2018.8709334

Bhagoji BS, Dhanalakshmi K (2019) Modified sigmoid based model and experimental analysis of SMA spring as variable stiffness actuator. Smart Struct Syst 24(3):361–377. https://doi.org/10.12989/sss.2019.24.3.361

Cebollada S, Payá L, Jiang X et al (2021) Development and use of a convolutional neural network for hierarchical appearance-based localization. Artif Intell Rev. https://doi.org/10.1007/s10462-021-10076-2

Chin K, Hellebrekers T, Carmel M (2020) Machine learning for soft robotic sensing and control. Adv Int Sys 2:1900171. https://doi.org/10.1002/aisy.201900171

Estibalitz A, Jorge F, Alfredo G-A, Victor E (2010) Sensor-less control of SMA-based actuators using neural networks. J Int Mat Sys Struct 21(8):1809–1818. https://doi.org/10.1177/1045389X1045389X1045389X1045389X

Gurang H, Banerjee A (2016) Self-sensing shape memory alloy wire actuator based on unscented Kalman filter. Sens Actuators, A 251:258–265

Hiraga M, Ohkura K (2021) Topology and weight evolving artificial neural networks in cooperative transport by a robotic swarm. Artif Life Robot. https://doi.org/10.1007/s10015-021-00716-9

Hu K, Rabenorosoa K, Ouisse M (2021) A review of SMA-based actuators for bidirectional rotational motion: application to origami robots. Front Robot AI 8:678486. https://doi.org/10.3389/frobt.2021.678486

Jiang L, Sakhare SR, Kaur M (2021) Impact of industrial 4.0 on environment along with correlation between economic growth and carbon emissions. Int J Syst Assur Eng Manag. https://doi.org/10.1007/s10766-021-01456-6

Kaur M, Kadam S (2019) Discovery of resources over Cloud using MADM approaches. Int J Eng Model 32(2-4):83–92. https://doi.org/10.31534/engmod.2019.2-4.r02m

Kaur M, Kadam S (2021) Bio-inspired workflow scheduling on HPC platforms. Teh Glas 15(1):60–68. https://doi.org/10.31803/tg-20210204183323

Miaolei Z, Yannan Z, Kun J, Dong Z (2017) Model reference adaptive control based on KP model for magnetically controlled shape memory alloy actuators. J App Bio Func Mat 15(1):531–537. https://doi.org/10.5301/abfm.5000364

Narayanan P, Mohammad E (2016) Control of a shape memory alloy-actuated rotary manipulator using an artificial neural network-based self-sensing technique. J Int Mat Sys Struct 27(14):1885–1894. https://doi.org/10.1177/1045389X15596626

Rahmani ME, Amine A, Fernandes JE (2021) Multi-stage genetic algorithm and deep neural network for robot execution failure detection. Neural Process Lett 53:4527–4547. https://doi.org/10.1007/s11063-021-10610-x

Senapati A, Nag A, Mondal A, Maji S (2021) A novel framework for COVID-19 case prediction through piecewise regression in India. Springer, Int J Inf Tecnol 13(1):41–48. https://doi.org/10.1007/s41870-020-00552-3

Sul BB, Subudhi CS, Dhanalakshmi K (2018) Neural network based displacement modeling of shape memory alloy spring actuator. IEEE Sensors 2018:1–4. https://doi.org/10.1109/ICSENS.2018.8589922

Szemenyi M, Estivill-Castro V (2021) Fully neural object detection solutions for robot soccer. Neural Comput Appl. https://doi.org/10.1007/s00521-021-00597-2

Wang T-M, Shi Z-Y, Liu D, Chen M, Zhang ZH (2012) An accurately controlled antagonistic shape memory alloy actuator with self-sensing. Sensors 12(6):7682–7700. https://doi.org/10.3390/s120607682

Yasuyuki S, Kagawa Y (2019) Dynamic tracking control of an SMA wire actuator based on model matching. Sens Actuators, A 292:129–136. https://doi.org/10.1016/j.sna.2019.04.011

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