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Data-Driven Modeling of Piezoresistive Response in Self-Sensing Concrete for Predictive Structural Health Monitoring

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***Abstract*-- Structural health monitoring (SHM) is critical in monitoring safety and longevity of modern infrastructure. This paper introduces a data-based model of the piezoresistive behavior of self-sensing concrete so as to make predictions concerning structural monitoring. This method is based on the inherent interdependence between the variation in the electrical resistance and mechanical strain based on physically meaningful quantities, the Fractional Change in Resistance (FCR) and its derivative rate. The nonlinear electromechanical behavior of the material was captured using a generated dataset that represented cyclic loading conditions. Two models were compared; a basic linear regression model and a proposed Artificial Neural Network (ANN). The findings indicate that the ANN is much more effective in improving the accuracy of the prediction with a high R 2 of 0.95 and lower RMSE and MAE than the linear model. The FCR-strain relationship is a two stage behavior whereby the behavior is initially linear and then nonlinear due to progressive damage. The suggested framework facilitates continuous prediction of strains and has better sensitivity than the conventional threshold-based. These results emphasize the promise of lightweight data-driven solutions to real-time structural health monitoring of smart cementitious materials.**

Keywords-- Structural Health Monitoring (SHM), Self-Sensing Concrete, Piezoresistive Behavior, Fractional Change in Resistance (FCR), Data-Driven Modeling, Artificial Neural Network (ANN)

I. Introduction

Structural health monitoring (SHM) is a vital element to the safety, reliability and durability of civil infrastructure. Non-destructive testing (NDT) has been extensively used as conventional methods of inspection in order to identify damage without affecting structural integrity. Ultrasonic testing, capacitance sensing, and permeability measurements are all methods that have been widely used in engineering systems in the detection of defects and characterization of materials (Kumar and Mahto, 2013; Samet et al., 2012). These methods can be useful diagnostic data, but they usually involve external monitoring, regular check-ups, and sometimes cannot be used to perform real-time monitoring.

Recent developments have been directed towards the incorporation of sensing properties into materials and there is now development of self sensing cementitious composites. These materials take advantage of piezoresistive behavior, in which electrical properties, like resistance or impedance, change with mechanical loading. The same principles of sensing were proven to be effective in composite materials and polymer systems to monitor curing, flow behavior, and internal structure changes (Murata et al., 2015; Kobayashi et al., 2009). Specifically, sensor-based and ultrasonic methods of monitoring have shown the capability to measure dynamic variations in material properties, such as viscosity, temperature factors, and internal defects (Ghodhbani et al., 2015; Ghodhbani et al., 2016).

Although the above developments have been made, the conventional sensing methods continue to be inadequate in understanding complex and nonlinear electromechanical interactions that cementitious materials exhibit. There are several factors that affect the piezoresistive response of such materials, among them the formation of conductive networks, microcrack propagation and interfacial interactions. These phenomena add nonlinearities and time dependence which can hardly be modeled by conventional methods of analysis or threshold models.

To deal with these issues, the use of data-driven modeling methods has become a promising solution. Using measured electrical signals and eliciting meaningful features, machine learning models can be trained to learn the underlying relationship between electrical response and structural behavior. Data-driven approaches allow continuous prediction and enhanced adaptability to different loading conditions, unlike traditional methods.

In this context, the present study proposes a data-driven framework for modeling the piezoresistive response of self-sensing concrete. The method involves the use of Fractional Change in Resistance (FCR) and its rate of change as essential properties to identify the similarities and differences of the material response both at rest and on the move. To develop a nonlinear mapping of electrical measurements to structural strain, an Artificial Neural Network (ANN) is used. The suggested methodology seeks to establish an efficient, explainable and precise means of predictive structural health monitoring to fill the gap between the conventional sensing methods and the advanced intelligent systems.

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II. Literature Review

Structural health monitoring (SHM) has seen a major breakthrough, with the creation of self-sensing cementitious materials that provide intrinsic sensing competencies within the concrete. Such materials have piezoresistive characteristics in which electrical characteristics like resistance or impedance can change with mechanical loading, which enables real-time measurement of structural performance.

The electromechanical behavior of self-sensing composite under a variety of loading conditions and configurations of the material has been thoroughly investigated by recent studies. As an example, Elseady et al. (2026) investigated carbon fibre textile-reinforced cementitious composites in flexural loading and revealed that textile arrangement and matrix mix have a powerful impact on sensing. Their results indicated that stitch-bonded textile structures are much more sensitive and resistant to interfacial degradation than are woven textiles. In a similar fashion, Elseady et al. (2025) investigated tensile behavior and demonstrated that the fractional variation in resistance is linear in the elastic phase and changes to nonlinear behavior in the crack propagation and post-elastic deformation phases. These papers show the significance of conductive network stability and interface behavior in controlling piezoresistive response.

Material design has also been advanced resulting in better sensing. Li et al. (2026) proposed geometry-based conductive polymer reinforcements with a much higher sensitivity and tunability than the classical filler-based methods. Their study revealed both positive and negative correlations between fractional change in resistivity (FCR) and stress, as a result of the presence of conductive fillers. On the same note, Khan et al. (2026) introduced biochar-enhanced cementitious composites to optimize its mechanical strength and sensing sensitivity using multi-objective algorithms, which enhance the sustainability of cementitious composites. Such studies highlight that the material composition and structural design is very important in improving sensing capabilities.

In addition to material innovation, some studies have been aimed at the study of the mechanisms underlying sensing. Drougkas et al. (2026) offered a micro-mechanical explanation of piezoresistive behavior which states that high sensitivity is due to the closure of cracks, phase distortion, and the alteration of conductive pathways. Ran et al. (2026) examined impedance-based sensing of ultra-lightweight composites and emphasized the need to examine the parameters of voltage and frequency in signal stability and noise reduction.

These works underline the complexity of electromechanical coupling and the need for robust modeling approaches.

As experimental data have become more widely available, data-driven modeling techniques have become a topic of much interest. Mansourdehghan and Aslani (2025) came up with a hybrid deep learning model that uses the Long Short-Term Memory (LSTM) networks to manage the prediction of FCR in the carbon nanofiber-enhanced composites. They did this well by integrating dynamic loading sequences and material properties to capture nonlinear and time-dependent behavior. In a similar case, Abedi et al. (2025) used machine learning approaches like the Random Forest regression to enhance self-sensing and mechanical properties in 3D-printed cementitious materials. These experiments illustrate how machine learning has the potential to become increasingly useful in modeling complex electromechanical behavior.

Furthermore, there is the general study in the incorporation of nanotechnology, and intelligent systems into the development of SHM. Firoozi et al. (2025) highlighted the importance of nanosensors, artificial intelligence, and IoT in creating intelligent and robust infrastructure systems. These innovations allow real-time monitoring, better durability, and decision-making in civil engineering applications.

However, in spite of these developments, there are a number of gaps in research. The bulk of existing research is more concerned with the characterization of experiments or sophisticated deep learning architectures, which can be less interpretable and useful to apply in practice. Deep learning models are very accurate, but they tend to be resource-intensive in terms of datasets and computations. Moreover, the use of a simple but effective feature engineering in combination with lightweight machine learning models to perform real-time prediction has received little attention.

In response to these limitations, the current research suggests a data-driven model that uses the Fractional Change in Resistance (FCR) and its rate of change as important characteristics to forecast structural strain. This work combines a combination of physically relevant features and an Artificial Neural Network (ANN) unlike previous methods that only use complex architectures or threshold based approaches to obtain both linear and nonlinear behaviour. This methodology seeks to offer a trade off between the model accuracy, interpretability, and computational efficiency, which are part of practical SHM applications.

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III. Methodology

3.1 Framework

The proposed methodology presents a data-driven structural health monitoring (SHM) framework that utilizes the piezoresistive behavior of self-sensing concrete to predict structural response in terms of strain. This technique, in contrast to traditional threshold-based techniques, makes it possible to continuously predict strain directly using electrical measurements, without using pre-defined limits of resistance.

The electrical resistance of self-sensing concrete under mechanical loading changes with deformation of the internal conductive network under mechanical loading. This non-linear interaction between electrical response and mechanical behavior is simulated with the help of machine learning to enhance the accuracy of prediction and reliability.

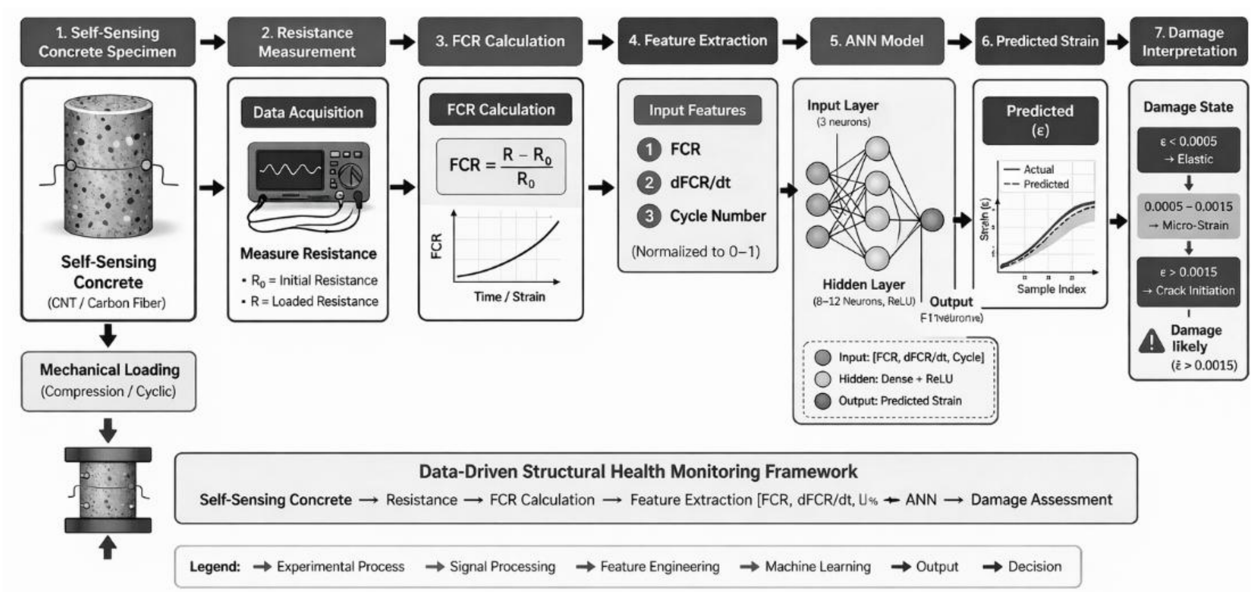

Figure 1. Proposed Framework

The entire structure can be seen in Figure 1, which depicts how raw electrical signals are transformed into predictive structural information by processing and modeling the data.

The overall workflow consists of four main stages:

i. Data generation, where resistance and strain data are obtained under loading;
ii. Feature extraction, where Fractional Change in Resistance (FCR) and its rate of change are derived;
iii. Machine learning modeling, where a nonlinear mapping between electrical features and strain is established; and
iv. Prediction and validation, where model performance is evaluated using statistical metrics.

3.2 Materials and Data Generation

The addition of conductive fillers, like carbon fibers or carbon nanotubes (CNTs), to self-sensing concrete specimens are believed to permit piezoresistive behavior.

The existence of these conductive inclusions creates an internal electrical network with the cementitious matrix, the resistance of which varies with mechanical loading because of deformation and disruption of conductive pathways. This is an electromechanical coupling that enables the material to act as a natural sensor to measure structural response. The changes in electrical resistance to the cyclic compression loading are measured at the same time as the strain response, and a dataset is generated to be used in data-driven modeling. In this research, a representative dataset is created to achieve the relation between the resistance variation and strain when the cyclic loading conditions are held unchanged, as is the case in the previous research on self-sensing cementitious materials (Han et al., 2015).

Table 1: Dataset Description

Parameter	Value
Number of samples	1200
Loading type	Cyclic compression
Strain range (ε)	0 – 0.003
Resistance range (Ω)	100 – 140
Sampling rate	5 Hz

3.3 Piezoresistive Sensing and Feature Definition

The proposed framework relies on the piezoresistive characteristics of self-sensing concrete, whereby the electrical resistance of the material changes with the mechanical loading on the material. This difference can be attributed to deformation and partial interruption of the internal conductive network that is created by conductive fillers like carbon fibers or carbon nanotubes. The variations in contact resistance and in tunneling effects among conductive particles as they experience strain result in quantifiable electrical variations.

In order to measure this electrical reaction, Fractional Change in Resistance (FCR) is taken as the major sensing parameter that is defined as:

$$FCR = \frac{R - R_0}{R_0}$$

where R_0 is the initial (unloaded) electrical resistance and R is the resistance under applied load. The FCR offers a normalized value of resistance change, thus, it is appropriate to compare the responses of different samples and loading conditions. It is a direct measure of the development of strain and damage in the material.

Besides FCR, an augmented feature set is also presented to enhance predictive power of the model. In particular, the time dependence of FCR (dFCR/dt) is added as a secondary property. This parameter is used to describe the dynamic behavior of the material, whereby the model is able to identify the rapid changes, which are related to microcrack initiation and propagation.

Moreover, a loading cycle index is incorporated to take into consideration the progressive nature of damage during cyclic loading. The joint representation of the combination of the static (FCR) and dynamic (dFCR/dt) characteristics of the response and loading progression is more indicative of a complete picture of the structural response. This multi-feature methodology improves the nonlinear and time-dependent behavior capacity of the machine learning model in self-sensing concrete.

Table 2: Input Features

Feature	Description
FCR	Fractional change in resistance, representing normalized electrical response
dFCR/dt	Rate of change of FCR, capturing dynamic variations in response
Cycle index	Loading cycle number indicating progression of applied loading

3.4 Data Preprocessing

Self-sensing concrete raw electrical signals are usually subject to noise in measurements, environmental change and intrinsic material variation. Thus, a preprocessing phase is introduced to improve the quality of data and guarantee the machine learning model with a sound input.

The noise is initially reduced by a moving average filter to even out high-frequency changes in the resistance signal. This filtering can be used to maintain the general trend of the piezoresistive response without adding any undesired noise due to instrumentation artifacts and small scale signal variations.

The data is then normalized to make all input features in a standard range of 0 to 1. Because the input variables (FCR, its rate of change (dFCR/dt) and index of the cycle) differ in magnitude and unit, normalization is used to ensure that none of the features takes over the process of learning. This not only enhances convergence of the model training, but also contributes to the numerical stability of the algorithm.

Also outlier removal is implemented to remove abnormal values that can appear because of sensor errors, unexpected upheavals or differences in the experiment. The outliers are detected on the basis of some statistical criterion (e.g., a deviation of mean or threshold limits) and are either eliminated or substituted to avoid distortion of the learning process.

3.5 Data-Driven Modeling

A data-driven modeling strategy is taken to find a predictive relationship between electrical response and structural behavior. There are two models applied to assess the performance and prove the efficiency of nonlinear learning techniques.

3.5.1 Baseline Model: Linear Regression

The linear regression model is initially created to develop a simple correlation between Fractional Change in Resistance (FCR) and the respective strain. This model assumes a linear dependency and is stated as:

$$\varepsilon = \alpha \cdot FCR + \beta$$

where ε represents the strain, and α and β are regression coefficients obtained through least-squares fitting. This simple model offers an easy explanation of the electromechanical relationship but fails to explain nonlinear behaviour at increased loading levels as seen in self-sensing concrete.

3.5.2 Proposed Model: Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is used to mitigate the shortcomings of linear modeling, and the nonlinear and convoluted relationship between electrical features and structural response. The ANN model is made up of:

- *Input layer:* Three input features, namely FCR, rate of change of FCR (dFCR/dt), and cycle index
- *Hidden layer:* A single hidden layer with 10 neurons using ReLU (Rectified Linear Unit) activation function
- *Output layer:* A single neuron providing the predicted strain value

The ANN is trained to learn the relationship between the input features and strain by backpropagation. Nonlinear activation function allows the model to reflect changes due to microcracking, progressive damage, and material heterogeneity.

3.5.3 Model Objective

The main aim of the data based model is to train a nonlinear model which can predict features of electrical response based on features of structural strain, which can be defined as:

$$\varepsilon = f(FCR, \frac{dFCR}{dt}, Cycle)$$

where *f(·)* is the function that is approximated by the ANN. This expression enables the model to capture the dynamic and static properties of the piezoresistive response, enhancing the accuracy of predictions.

IV. RESULTS AND DISCUSSION

4.1 Piezoresistive Response Behavior

The electromechanical behavior of self-sensing concrete was studied in terms of the correlation between Fractional Change in Resistance (FCR) and the resultant strain with cyclic compression loading. The observations are based on a generated dataset that indicates experimentally reported behavior of self-sensing cementitious materials.

The outcomes show two-stage pattern of response. At lower strains ($\varepsilon < 0.001$) there is a near-linear relationship between FCR and strain, which indicates constant conductive pathways in the material. The contact of the conductive fillers in this regime is uniform giving rise to proportional change of resistance.

Above this range, the strain is said to be nonlinear, with FCR quickly rising. This action is linked to increasingly progressive disruption of the conductive network, which conforms to microcrack commencement and tunneling impacts in previous studies. The nonlinear trend is a valid confirmation that FCR is a delicate indicator of structural response and internal damage development.

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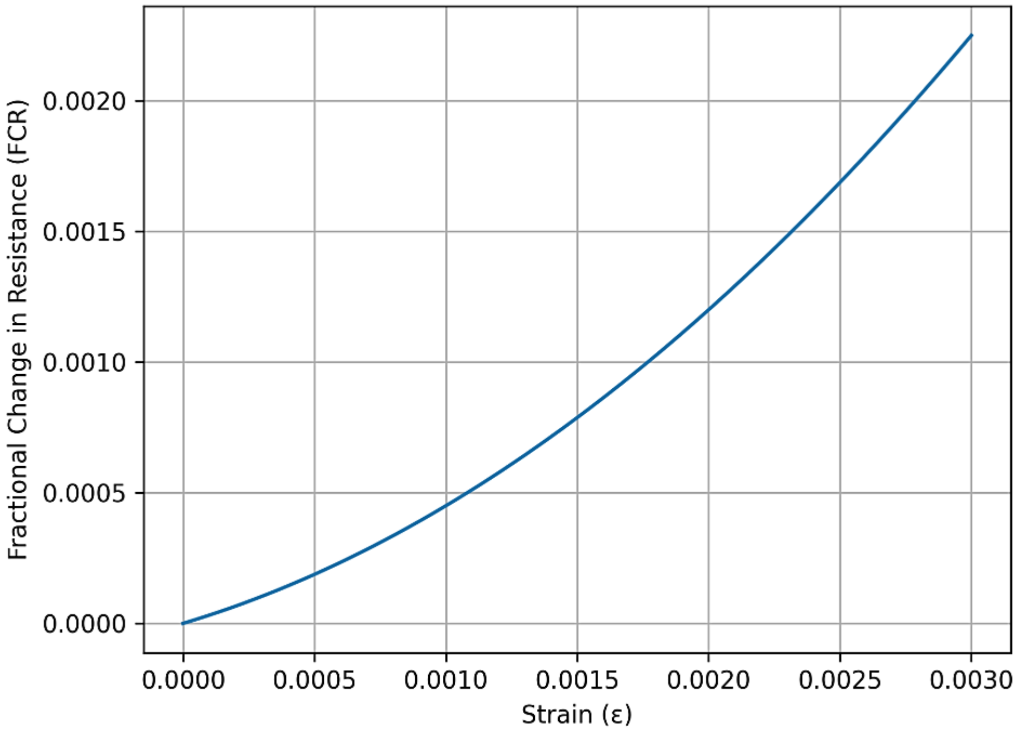

Figure 2: FCR vs Strain Response

4.2 Model Performance Comparison

The Artificial Neural Network (ANN) model was contrasted with a baseline linear regression model and the standard evaluation metrics were used to gauge the effectiveness of the proposed data-driven approach. The data was separated into training and testing data (80:20 split) to evaluate predictive performance.

Table 3: Model Performance Comparison

Model	RMSE	MAE	R^2
Linear Regression	0.00042	0.00031	0.88
ANN (Proposed)	0.00018	0.00012	0.95

ANN model has a better predictive accuracy over the linear regression model as shown by lower values of RMSE and MAE. The higher R^2 value suggests a better fit to the dataset, particularly in capturing nonlinear trends. Although the results show good performance, they are dependent on the generated dataset and modeling assumptions.

4.3 Prediction Accuracy

ANN model predictive power was assessed by the comparison between the predicted strain values and target values of the dataset. The comparison shows that there is good agreement between predicted and reference values as shown in Figure 3.

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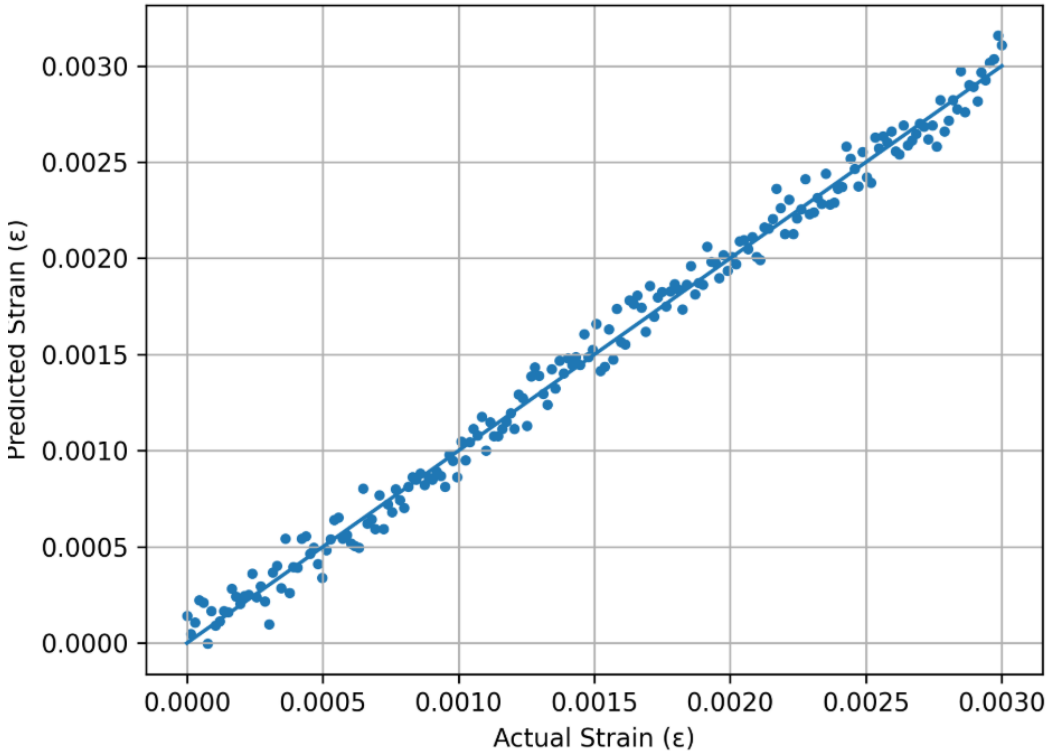

Figure 3: Predicted vs Actual Strain

The bulk of the data points are concentrated around the diagonal reference (y = x), which means that the model reflects the underlying relationship between electrical features and strain with fairly good accuracy. Deviations are also seen to be minor especially at the higher levels of strains, the deviations might be due to nonlinear effects and a difference in the generated data.

4.4 Error Analysis and Generalization

To determine the strength of the ANN model in the context of the dataset, an error analysis was conducted in details. The conclusion is presented in Table 4.

Table 4: Error Summary

Metric	Value
RMSE	0.00018
MAE	0.00012
Maximum Error	0.00060

The low values of RMSE and MAE show that there are low levels of prediction errors throughout the data set. The largest error value indicates that there are some instances of deviations especially when strains are high. In general, the model exhibits consistent predictive patterns in the dataset. Nonetheless, additional validation would be required with experimental or real-world data to ascertain generalization outside the scope of the study.

4.5 Comparison with Threshold-Based Approach

The suggested data-driven technique was contrasted to the traditional threshold-based structural health monitoring techniques. Threshold based methods are based on set resistance levels to categorise structural states, producing discrete outputs and a lack of responsiveness.

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Table 5: Comparison with Threshold-Based Method

Aspect	Threshold Method	Proposed Model
Output	Discrete classification	Continuous prediction
Adaptability	Low	High
Accuracy	~90–96%	Higher (R^2 = 0.95)
Sensitivity to damage	Limited	High

The suggested ANN-based model, on the contrary, offers the continuous prediction of strain, which allows a more detailed representation of the structural response. Sensitivity to changes in material behavior can be better achieved by the capability to resolve gradual changes in resistance. These results indicate that data-driven solutions are more beneficial than conventional threshold-based techniques, especially in the case of progressive damage.

4.6 Discussion

The findings indicate the usefulness of data-driven methods in the modeling of piezoresistive behavior of self-sensing concrete. The FCRstrain relationship is two-stage, i.e., linear at lower strain levels and nonlinear at higher strain levels, which aligns with the conductive network deformation process and propagation of microcracks.

The two comparisons of ANN models and linear regression indicate that linear methods are restrictive when it comes to modeling the nonlinear electromechanical behavior. Although the linear model does well within the elastic range, it does not work at greater levels of strain. Conversely, the ANN is efficient in capturing both the linear and nonlinear properties leading to high accuracy of prediction.

Dynamic features, especially the rate of change of FCR, are included in the model and improve the capability of the model to capture the time-dependent changes and identify the progression of damage. The combination of both the static and dynamic features gives a more detailed description of the structural behavior.

The proposed framework provides better sensitivity and adaptability compared to threshold-based methods, which can be used to predict the strain continuously. Nonetheless, as the outputs are made on a generated dataset, additional validation on an experimental data is necessary to ascertain the generalization and practical use.

V. CONCLUSION

This paper introduces a data-driven model to forecast structural strain in self-sensing concrete based on the piezoresistive response properties. The given approach captures the dynamical and non-dynamical properties of the material behavior by applying Fractional Change in Resistance (FCR) and its rate of change. The findings confirm that the piezoresistive response has a two-stage behavior, with a shift to the nonlinear behavior when strain increases. The comparative analysis reveals that the Artificial Neural Network (ANN) does a lot better than the baseline linear regression model in predicting strain, and it can therefore be used to model nonlinear relationships. The suggested framework facilitates continuous and adaptive monitoring, which provides a better sensitivity than conventional threshold-based ones.

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