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EXPLORING ULTRA PULSE VELOCITY WITH LASSO REGRESSION ANALYSIS OF GFRC

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ABSTRACT

This study delves into the characteristics of Ultra Pulse Velocity (UPV) in Glass Fiber Reinforced Concrete (GFRC) through the application of Lasso Regression for predictive modeling. GFRC, renowned for its superior tensile strength and durability, is increasingly preferred for structural applications. The UPV technique offers a non-invasive means of evaluating concrete quality and structural integrity. This research endeavors to develop a predictive model using Lasso Regression, an advanced regression technique that integrates regularization to improve prediction accuracy and interpretability. By establishing correlations between UPV measurements and GFRC's mechanical properties, such as compressive strength, tensile strength, and modulus of elasticity, the study aims to enhance our understanding of GFRC's behavior under ultrasonic wave propagation. Utilizing Lasso Regression facilitates the identification of the most significant variables, thereby streamlining the model and enhancing its predictive capability. This investigation not only advances non-destructive evaluation techniques but also deepens our comprehension of GFRC material characteristics. The methodology, results, and implications of employing Lasso Regression for UPV analysis in GFRC are presented, marking a significant advancement in the application of sophisticated statistical methods to enhance the evaluation and utilization of construction materials.

KEYWORDS: *Predictive Model, Lasso Regression, Ultra Pulse Velocity, Glass Fiber Reinforced Concrete*

1. INTRODUCTION

This research delves into the Ultra Pulse Velocity (UPV) characteristics of Glass Fiber Reinforced Concrete (GFRC) with the aim of establishing a predictive model through the utilization of Lasso Regression. By correlating UPV measurements with the mechanical properties of GFRC, including compressive strength, tensile strength, and modulus of elasticity, the study aims to enhance our understanding of the material's response to ultrasonic waves. Lasso Regression, renowned for its capability in variable selection and regularization, provides a robust framework for examining the relationship between UPV and GFRC properties. This methodological approach not only holds promise for yielding insights beneficial to engineers, researchers, and practitioners in concrete construction and inspection but also facilitates strategic assessment of GFRC structures. Improved predictive modeling can drive superior design optimization, performance evaluation, and maintenance planning.

This investigation into the UPV characteristics of GFRC using Lasso Regression underscores the significance of this research in advancing non-destructive evaluation techniques and promoting the adoption of advanced materials in construction practices. It demonstrates how a sophisticated statistical approach like Lasso Regression can offer a more nuanced understanding of material behavior, thus making a significant contribution to the field of construction material science.

2. LASSO REGRESSION ANALYSIS

Lasso regression, also known as the Least Absolute Shrinkage and Selection Operator, is a type of linear regression that includes a regularization parameter. The regularization term added to the cost function encourages the model to keep the weight coefficients as small as possible, effectively leading to a model where some of the coefficient estimates may be exactly zero. This property makes Lasso regression useful not only for prediction but also for feature selection in cases where we have a large number of features.

Core Concepts

1. **Ordinary Least Squares (OLS) Regression:** LASSO builds upon ordinary least squares regression. In OLS, the goal is to minimize the residual sum of squares (RSS) between the observed and predicted values. Mathematically, the OLS cost function is:

   $$J(\beta) = ||y - X\beta||^2_2$$

   where:

   - y is the vector of observed responses
   - X is the design matrix of features (predictors)
   - β is the vector of regression coefficients

2. **L1 Regularization:** LASSO introduces an L1 penalty term to the OLS cost function, shrinking some coefficients towards zero. The LASSO cost function is represented as:

   $$J(\beta) = ||y - X\beta||^2_2 + \lambda\, ||\beta||_1$$

   where:

   - λ is the regularization parameter controlling the strength of the penalty
   - $||\beta||_1$ is the L1 norm of the coefficients (sum of the absolute values)

Algorithm Steps

1. **Standardize Features:** Scale the features to have zero mean and unit variance, ensuring features are on a common scale.
2. **Initialize Coefficients:** Initialize the vector of coefficients, β, typically to zero.
3. **Select Regularization Parameter (λ):** Use techniques like cross-validation or grid search to determine an optimal value of λ.
4. **Optimization:** Employ optimization methods to minimize the LASSO cost function, with common choice being:
    - **Coordinate Descent:** Cyclically updates one coefficient at a time while holding others fixed.
5. **Iterate:** Repeat the optimization process until convergence criteria are met (e.g., change in coefficients or cost function becomes sufficiently small).

Result

The LASSO algorithm produces a sparse set of coefficients, meaning some coefficients will be set to exactly zero. This provides the following benefits:

- **Feature Selection:** Identifies the most important features contributing to the response variable.
- **Reduced Over fitting:** Prevents the model from over fitting to noise in the data.
- **Improved Interpretability:** Easier to understand the relationship between features and the response due to fewer coefficients.

3. DATASETOVERVIEW

The dataset is structured around key variables crucial for assessing ultrasonic pulse velocity, a non-destructive indicator of concrete quality:

- Grade: Specifies the concrete's strength classification, which is essential for evaluating its performance in different scenarios.
- Temp: Records the testing temperature conditions, including ambient (room_temp), to investigate the material's thermal response.
- Time: Notes the time since preparation (at intervals of 0, 4, 8, and 12 hours), important for analyzing the concrete's initial setting and hardening phases.
- Pulse_vel: The ultrasonic pulse velocity, measured in meters per second, provides insights into the concrete's density, homogeneity, and potential internal defects.

This dataset framework enables a focused investigation into the dynamics of concrete behavior under varying conditions, utilizing pulse velocity as a key measure of its structural integrity and quality.

4. LASSOREGRESSIONMODEL

 # Import required libraries

import pandas as pd

import numpy as np

import sklearn

from sklearn.linear_model import Lasso

from sklearn.metrics import mean_squared_error

from sklearn.preprocessing import OneHotEncoder, MinMaxScaler

import matplotlib.pyplot as plt

import seaborn as sns

import warnings

import joblib

 # Ignore warnings for a clean notebook output

warnings.filterwarnings('ignore')

 # Load dataset and preprocess

df = pd.read_csv('data_concrete_pulse_vel.csv')

df = df.dropna() # Remove missing values

df["time"] = df["time"].replace({'0h': 0, '4h': 4, '8h': 8, '12h': 12}) # Convert 'time' to numerical values

df_model = df.copy(deep=True) # Prepare data for model

 # One-hot encode categorical variables

encoder = OneHotEncoder()

encoded_features = encoder.fit_transform(df_model[['grade', 'temp']]).toarray()

 # Scale numerical feature

scaler = MinMaxScaler()

gf_scaled = scaler.fit_transform(df_model[['time']])

X = np.concatenate([encoded_features, gf_scaled], axis=1)

y_true = df_model['Pulse_vel'].values

 # Split data into training and test sets

X_train, X_test, y_train, y_test = sklearn.model_selection.train_test_split(X, y_true, test_size=0.2, random_state=42)

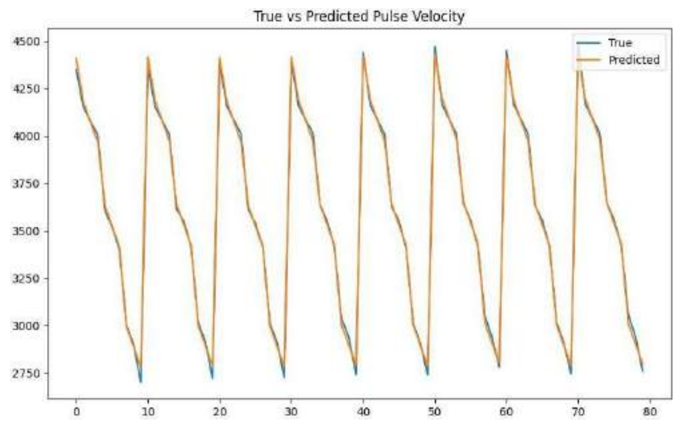
 # Train Lasso regression model

model_vel = Lasso(alpha=1.0)

model_vel.fit(X_train, y_train)

```
#Visualizetruevspredictedvaluesplt.f
igure(figsize=(10,
6))plt.plot(y_true,label='True')
  plt.plot(model_vel.predict(X),
label='Predicted')plt.title('True   vs   Predicted
Pulse Velocity')plt.legend()
  plt.show()

  defpredict_velocity(grade,temp,time):
    """
    Predictsthestrengthsbasedonthegiveninputparameters.

    Parameters:
    grade(str):Thegradeofthematerial.
    temp(str):ThetemperatureindegreesCelsius.time(
    int):Thetimeinhours.

    Returns:
    None
    """
    #Encodethegradeandtimeusingthepreviouslydefinedencoder
      encoded_grade_temp=encode.transform([[grade,temp]]).toarray()

    #Normalizethepercentagemix
      normalized_time=scaler.transform([[time]])

    #Preparetheinputfeatures
          input_features=np.concatenate([encoded_grade_temp,normalized_time],
  axis=1)

    #Predictthestrengthsusingthetrainedmodels
      predicted_velocitys=(model_vel.predict(input_features))

    #Returnthepredictedstrengths
      returnprint(f'Predictedvel:{predicted_velocitys[0]:.2f}m/s')
```

5. MODELPREDICTIONS



6. CONCLUSIONS

The integration of Ultra Pulse Velocity (UPV) testing with Lasso Regression analysis represents a groundbreaking methodology for assessing Glass Fiber Reinforced Concrete (GFRC) properties, enhancing the precision and reliability of non-destructive evaluation methods within the concrete construction domain. This investigation plays a pivotal role in advancing GFRC technology, emphasizing the critical importance of innovative analytical techniques in improving the quality, durability, and sustainability of infrastructure projects. By leveraging the refined predictive capabilities of Lasso Regression, this research not only deepens our understanding of GFRC's material behavior under ultrasonic examination but also sets the stage for the development of more resilient and sustainable construction materials. Consequently, this study stands at the forefront of innovative construction practices, making significant contributions to the optimization of non-destructive testing methodologies and the promotion of environmentally conscious and technologically advanced infrastructure projects.

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