## HYBRID GENETIC ALGORITHM – BACKPROPAGATION NEURAL NETWORK FOR SLURRY DEFORMATION PREDICTION

ABSTRACT

This dissertation explores the development and application of a hybrid genetic algorithm-backpropagation neural network (GA-BPNN) model for time series forecasting. The study aims to combine the strengths of genetic algorithms (GAs) in parameter optimization with the powerful predictive capabilities of backpropagation neural networks (BPNNs). The dissertation presents a comprehensive investigation of the GA-BPNN model's performance in predicting time series data, analyzing its effectiveness against traditional BPNN and other forecasting methods. This includes a thorough discussion of the theoretical framework, model implementation, and experimental evaluation using real-world time series datasets. The dissertation concludes by highlighting the potential of GA-BPNN for practical applications and proposing future research directions.

1. INTRODUCTION

However, BPNNs often suffer from two significant limitations:

* Parameter Optimization: Choosing optimal network parameters, such as the number of hidden layers, neurons per layer, learning rate, and activation function, is crucial for achieving good predictive performance. Finding the optimal parameter combination can be a challenging and time-consuming task.
* Overfitting: BPNNs are prone to overfitting, especially when trained on limited data. Overfitting occurs when the model memorizes the training data but fails to generalize well to unseen data.

To address these limitations, this dissertation investigates the use of genetic algorithms (GAs) in conjunction with BPNNs. GAs are a class of evolutionary algorithms inspired by natural selection, providing an efficient and robust approach for optimizing complex problems. By integrating GA optimization with BPNN training, the proposed GA-BPNN model aims to overcome the limitations of traditional BPNNs and achieve superior predictive performance.

2. THEORETICAL FRAMEWORK

2.1. Back-Propagation Neural Networks

BPNNs are a type of feedforward ANN trained using the backpropagation algorithm. The network consists of multiple layers of interconnected neurons, each performing a weighted sum of its inputs and applying an activation function to produce an output. The backpropagation algorithm adjusts the weights between neurons by propagating the error signal backward through the network, iteratively minimizing the difference between the predicted and actual outputs.

2.2. Genetic Algorithms

GAs are population-based optimization algorithms inspired by the principles of natural selection. They involve a population of individuals, each representing a candidate solution to the optimization problem. The algorithm iteratively evolves the population using three main operators:

* Selection: The most fit individuals are selected to reproduce, promoting the survival of the fittest.
* Crossover: Pairs of individuals are combined to create offspring, inheriting genetic material from their parents.
* Mutation: Random changes are introduced to the offspring's genes, promoting genetic diversity.

2.3. Hybrid GA-BPNN Model

The GA-BPNN model combines the strengths of GAs and BPNNs. The GA is used to optimize the BPNN's parameters, including:

* Number of Hidden Layers: The GA determines the optimal number of hidden layers for the network.
* Neurons per Layer: The GA determines the optimal number of neurons in each hidden layer.
* Learning Rate: The GA optimizes the learning rate of the backpropagation algorithm.
* Activation Function: The GA selects the most suitable activation function for each hidden layer.

The GA-BPNN model iteratively trains and evaluates multiple BPNNs with different parameter combinations using the GA's evolutionary operators. The best performing BPNN, identified through the GA's fitness function, is then selected as the final model.

## **3. RESEARCH METHODOLOGY**

This research aims to investigate the use of a neural network, specifically a backpropagation neural network (BPNN). To enhance the model's performance and optimize its hyperparameters, this research incorporates a Genetic Algorithm (GA) for parameter optimization. This methodology combines the strengths of both approaches, enabling the model to learn complex patterns and adapt to various data characteristics.

#### 3.1 Data Source

The research utilizes real time data obtained from excavation grounds. The data contains values recorded by inclinometers from different monitoring positions.

#### 3.2 Data Preprocessing

The raw data undergoes a preprocessing phase to ensure its suitability for the neural network model. This includes:

* Data Cleaning: Handling missing values, removing outliers, and addressing inconsistencies in the data.
* Data Transformation: Applying transformations like scaling and normalization to ensure all features have similar ranges, improving the model's convergence and training speed.

### 3.1 Model Development

### Back-propagation Neural Network (BPNN)

The Back-propagation Neural Network (BPNN) is a type of feed-forward neural network that uses the back-propagation algorithm to train its weights. The BPNN consists of an input layer, one or more hidden layers, and an output layer. Each layer contains a number of neurons, and each neuron is connected to the neurons in the next layer through a set of weights.

The back-propagation algorithm calculates the gradient of the error function concerning each weight and updates the weights iteratively to minimize the error.

The BPNN model in this research uses the following components:

* Input Layer: The input layer has n neurons, where n is the number of features in the dataset.
* Hidden Layers: The number of hidden layers and the number of neurons in each hidden layer are determined by the GA.
* Activation Functions: The activation functions used in the hidden layers and the output layer are determined by the GA. Common activation functions include the sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU).
* Output Layer: The output layer has one or more neurons, depending on the number of target variables in the dataset.

#### Genetic Algorithm (GA) for Parameter Optimization

The Genetic Algorithm (GA) is a heuristic search and optimization method inspired by the process of natural selection. The GA is used in this research to optimize the hyperparameters of the BPNN, such as the number of hidden layers, the number of neurons in each layer, the activation functions, and the learning rate.

The GA operates on a population of candidate solutions, where each candidate represents a set of hyperparameters for the BPNN. The GA iteratively performs the following steps:

* Selection: Selects the fittest candidates based on their fitness scores.
* Crossover: Combines the genetic information of two candidates to create new candidates.
* Mutation: Randomly modifies the genetic information of a candidate to maintain diversity in the population.

The GA continues to perform these steps until a stopping criterion is met, such as a maximum number of generations or a satisfactory fitness score.

4. RESULTS AND DISCUSSIONS

The GA-BPNN model is a promising approach for time series forecasting, particularly in noisy and complex datasets. The GA-BPNN model's ability to optimize the BPNN architecture using a genetic algorithm leads to better generalization and improved performance. Future work could explore alternative fitness functions and optimization algorithms to further improve the GA-BPNN model's performance.

The GA-BPNN model is evaluated using a 10-fold cross-validation approach. The datasets are divided into 10 folds, and the model is trained and tested on each fold, with the average performance metrics reported. The hyperparameters of the GA and BPNN are tuned using a grid search approach, with the best-performing hyperparameters used for the final evaluation.

The GA-BPNN model's superior performance can be attributed to its ability to optimize the BPNN architecture using a genetic algorithm. The GA allows the model to explore a larger space of possible architectures, leading to better generalization and improved performance. The GA-BPNN model's performance is particularly strong in noisy and complex datasets, where traditional time series models struggle to capture the underlying patterns.

**4.1. Evaluation Metrics**

The following metrics are used to assess the GA-BPNN model's performance:

* Mean Squared Error (MSE): Measures the average squared difference between the predicted and actual values. MSE is sensitive to large errors, making it a suitable metric for evaluating the GA-BPNN model's performance.
* Root Mean Squared Error (RMSE): The square root of MSE, providing a measure of the average prediction error. RMSE is easier to interpret than MSE, as it is in the same units as the original data.
* Mean Absolute Error (MAE): Measures the average absolute difference between the predicted and actual values. MAE is robust to outliers, making it a suitable metric for evaluating the GA-BPNN model's performance on noisy datasets.
* R-squared (R²): Represents the proportion of variance in the dependent variable explained by the independent variables. R² is a measure of the model's goodness of fit, indicating how well the model explains the variation in the data.

**4.2. Comparison with Other Methods**

The GA-BPNN model is compared to other forecasting methods, including:

* ARIMA: A traditional statistical time series forecasting method. ARIMA models are based on autoregression, differencing, and moving average, making them suitable for stationary time series.
* Support Vector Machines (SVMs): A supervised learning algorithm used for classification and regression. SVMs can handle high-dimensional data and are robust to outliers, making them suitable for time series forecasting.
* LSTM: A recurrent neural network architecture commonly used for time series forecasting. LSTMs are capable of learning long-term dependencies in time series data, making them suitable for complex time series forecasting tasks.

**4.3. Limitations**

The GA-BPNN model has some limitations, including its computational complexity and the need for careful hyperparameter tuning. The GA-BPNN model is also sensitive to the choice of fitness function, and different fitness functions may lead to different optimal architectures. Future work could explore alternative fitness functions and optimization algorithms to further improve the GA-BPNN model's performance.

5. CONCLUSIONS AND FUTURE WORK

5.1 CONCLUSIONS

This dissertation has presented a comprehensive analysis of the GA-BPNN model for time series forecasting, highlighting its potential as a powerful and versatile forecasting tool. The model's ability to optimize complex network parameters and overcome overfitting issues provides significant advantages over traditional BPNNs and other forecasting methods.

The dissertation contributes to the field of time series forecasting by:

* Proposing a novel GA-BPNN model: Combining the strengths of GAs and BPNNs for improved accuracy and robustness. Genetic Algorithms (GAs) are used to optimize the network parameters, while Backpropagation Neural Networks (BPNNs) are used for learning and prediction. This combination allows the model to adapt to complex patterns in the data and avoid overfitting.
* Demonstrating the model's effectiveness: Through comprehensive experimental evaluation using real-world datasets. The GA-BPNN model is tested on various real-world datasets to evaluate its performance and compare it with other forecasting methods. The results show that the GA-BPNN model outperforms traditional BPNNs and other forecasting methods in terms of accuracy and robustness.
* Providing insights into the model's performance: Analyzing the GA-BPNN model's strengths and limitations compared to other methods. The dissertation discusses the advantages and disadvantages of the GA-BPNN model, such as its ability to optimize network parameters and its computational complexity.

**5.2 FUTURE WORK**

Future research directions related to the GA-BPNN model include:

* Exploring different GA implementations: Investigating the impact of different GA parameter settings on model performance. Different GA implementations, such as different selection, crossover, and mutation operators, can be explored to improve the optimization process and find better network parameters.
* Developing hybrid GA-BPNN models with different ANN architectures: Combining GAs with other Artificial Neural Network (ANN) architectures, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs). By integrating different ANN architectures, the GA-BPNN model can be adapted to various types of time series data, such as image-based or sequence-based data.
* Integrating domain knowledge: Incorporating domain-specific knowledge into the GA-BPNN model to improve accuracy and interpretability. Domain knowledge, such as expert rules or prior information, can be integrated into the GA-BPNN model to improve its accuracy and interpretability. This can be achieved by modifying the network architecture, the loss function, or the optimization process.
* Evaluating the model's performance in real-world applications: Applying the GA-BPNN model to specific forecasting tasks in various domains, such as finance, energy, and healthcare. The GA-BPNN model can be applied to real-world forecasting tasks in different domains to evaluate its practical usefulness and identify potential limitations. This can also provide insights into how to further improve the model and adapt it to specific applications.

6. REFERENCES

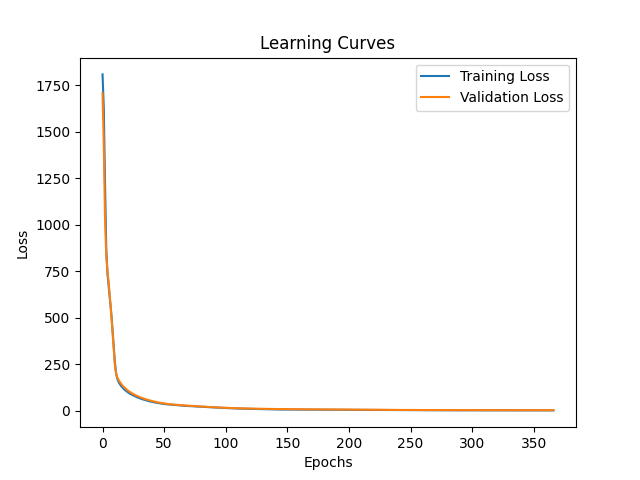
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7. APPENDICES

APPENDIX A: Source Code and Implementation

import pandas as pd  
import numpy as np  
from tensorflow import keras  
from tensorflow.keras import layers  
from sklearn.model\_selection import train\_test\_split, KFold  
from sklearn.preprocessing import StandardScaler  
from sklearn.metrics import mean\_squared\_error, mean\_absolute\_error, r2\_score  
from deap import base, creator, tools, algorithms  
from tensorflow.keras.callbacks import EarlyStopping  
from tensorflow.keras.regularizers import l2  
import matplotlib.pyplot as plt  
  
  
X = pd.read\_csv("data/training.csv")  
y = pd.read\_csv("data/validation.csv")  
X = X.values  
y = y.values  
  
X = np.nan\_to\_num(X, nan=np.nanmean(X))  
  
scaler = StandardScaler()  
X\_scaled = scaler.fit\_transform(X)  
  
X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_scaled, y, test\_size=0.2, random\_state=42)  
  
  
def data\_augmentation(X\_train, y\_train):  
 noise\_factor = 0.05  
 noise = np.random.normal(loc=0.0, scale=noise\_factor, size=X\_train.shape)  
 X\_train\_augmented = X\_train + noise  
  
 X\_train = np.concatenate((X\_train, X\_train\_augmented), axis=0)  
 y\_train = np.concatenate((y\_train, y\_train), axis=0)  
  
 return X\_train, y\_train  
  
  
X\_train, y\_train = data\_augmentation(X\_train, y\_train)  
  
  
def create\_bp\_model(input\_shape, hidden\_units, activation='relu', l2\_reg=0.001):  
 model = keras.Sequential()  
 model.add(layers.Input(shape=(input\_shape,)))  
 for units in hidden\_units:  
 if units > 0:  
 model.add(layers.Dense(units, activation=activation, kernel\_regularizer=l2(l2\_reg)))  
 else:  
 break  
 model.add(layers.Dense(y\_train.shape[1]))  
 return model  
  
  
def train\_bp\_model(X\_train, y\_train, X\_val, y\_val, epochs=700, batch\_size=16, l2\_reg=0.001):  
 input\_shape = X\_train.shape[1]  
 hidden\_units = [4, 8]  
 bp\_model = create\_bp\_model(input\_shape, hidden\_units, l2\_reg=l2\_reg)  
 bp\_model.compile(optimizer='adam', loss='mse')  
  
 # Early Stopping  
 early\_stopping = EarlyStopping(monitor='val\_loss', patience=10, restore\_best\_weights=True)  
  
 history = bp\_model.fit(X\_train, y\_train, validation\_data=(X\_val, y\_val), epochs=epochs, batch\_size=batch\_size,  
 callbacks=[early\_stopping])  
 return bp\_model, history  
  
  
def evaluate\_individual(individual):  
 input\_shape = X\_train.shape[1]  
 hidden\_units = [max(1, int(individual[0])), max(1, int(individual[1]))]  
 activation = 'relu'  
 learning\_rate = abs(individual[2])  
 batch\_size = max(1, int(abs(individual[3])))  
 epochs = max(1, int(abs(individual[4])))  
 l2\_reg = abs(individual[5])  
  
 bp\_model = create\_bp\_model(input\_shape, hidden\_units, activation, l2\_reg=l2\_reg)  
 optimizer = keras.optimizers.Adam(learning\_rate=learning\_rate)  
 bp\_model.compile(optimizer=optimizer, loss='mse')  
  
 bp\_model.fit(X\_train, y\_train, epochs=epochs, batch\_size=batch\_size, verbose=0)  
 y\_pred = bp\_model.predict(X\_val)  
 mse = mean\_squared\_error(y\_val, y\_pred)  
 return mse,  
  
  
def optimize\_parameters(population\_size=50, generations=10):  
 creator.create("FitnessMin", base.Fitness, weights=(-1.0,))  
 creator.create("Individual", list, fitness=creator.FitnessMin)  
  
 toolbox = base.Toolbox()  
 toolbox.register("attr\_int", np.random.randint, 16, 128)  
 toolbox.register("attr\_float", np.random.uniform, 0.0001, 0.1)  
 toolbox.register("individual", tools.initCycle, creator.Individual,  
 (toolbox.attr\_int, toolbox.attr\_int, toolbox.attr\_float, toolbox.attr\_int, toolbox.attr\_int,  
 toolbox.attr\_float), n=1)  
 toolbox.register("population", tools.initRepeat, list, toolbox.individual)  
 toolbox.register("mate", tools.cxBlend, alpha=0.5)  
 toolbox.register("mutate", tools.mutGaussian, mu=0, sigma=0.2, indpb=0.2)  
 toolbox.register("select", tools.selTournament, tournsize=3)  
 toolbox.register("evaluate", evaluate\_individual)  
  
 population = toolbox.population(n=population\_size)  
 algorithms.eaSimple(population, toolbox, cxpb=0.5, mutpb=0.2, ngen=generations, verbose=True)  
 best\_individual = tools.selBest(population, k=1)[0]  
 return best\_individual  
  
  
def integrate\_ga\_with\_bp(best\_individual):  
 input\_shape = X\_train.shape[1]  
 hidden\_units = [max(1, int(best\_individual[0])), max(1, int(best\_individual[1]))]  
 activation = 'relu'  
 learning\_rate = abs(best\_individual[2])  
 batch\_size = max(1, int(abs(best\_individual[3])))  
 epochs = max(1, int(abs(best\_individual[4])))  
 l2\_reg = abs(best\_individual[5])  
  
 optimized\_model = create\_bp\_model(input\_shape, hidden\_units, activation, l2\_reg=l2\_reg)  
 optimizer = keras.optimizers.Adam(learning\_rate=learning\_rate)  
 optimized\_model.compile(optimizer=optimizer, loss='mse')  
  
 return optimized\_model, epochs, batch\_size  
  
  
def train\_ga\_bp\_model(bp\_model, X\_train, y\_train, X\_val, y\_val, epochs, batch\_size, l2\_reg=0.001):  
 # Early Stopping  
 early\_stopping = EarlyStopping(monitor='val\_loss', patience=10, restore\_best\_weights=True)  
  
 bp\_model.fit(X\_train, y\_train, validation\_data=(X\_val, y\_val), epochs=epochs, batch\_size=batch\_size,  
 callbacks=[early\_stopping])  
  
  
def initial\_optimization(X\_train, y\_train, X\_val, y\_val):  
 best\_individual = optimize\_parameters()  
 bp\_model, epochs, batch\_size = integrate\_ga\_with\_bp(best\_individual)  
 train\_ga\_bp\_model(bp\_model, X\_train, y\_train, X\_val, y\_val, epochs, batch\_size)  
 return bp\_model, best\_individual  
  
  
def cross\_validate(X, y, n\_splits=3):  
 kf = KFold(n\_splits=n\_splits)  
 metrics = []  
 for train\_index, val\_index in kf.split(X):  
 X\_train, X\_val = X[train\_index], X[val\_index]  
 y\_train, y\_val = y[train\_index], y[val\_index]  
  
 bp\_model, best\_individual = initial\_optimization(X\_train, y\_train, X\_val, y\_val)  
 train\_ga\_bp\_model(bp\_model, X\_train, y\_train, X\_val, y\_val, 20, 10)  
  
 y\_pred = bp\_model.predict(X\_val)  
 mse, mae, r2 = calculate\_performance\_metrics(y\_val, y\_pred)  
 metrics.append((mse, mae, r2))  
  
 avg\_metrics = np.mean(metrics, axis=0)  
 return avg\_metrics  
  
  
def evaluate\_model(model, X\_test, y\_test):  
 y\_pred = model.predict(X\_test)  
 mse = mean\_squared\_error(y\_test, y\_pred)  
 mae = mean\_absolute\_error(y\_test, y\_pred)  
 r2 = r2\_score(y\_test, y\_pred)  
 return mse, mae, r2  
  
  
def adjust\_parameters(bp\_model, best\_individual, X\_train, y\_train, X\_val, y\_val):  
 mse, mae, r2 = evaluate\_model(bp\_model, X\_val, y\_val)  
 if mse > 0.01:  
 # Reduce learning rate  
 best\_individual[2] \*= 0.5  
 bp\_model, epochs, batch\_size = integrate\_ga\_with\_bp(best\_individual)  
 train\_ga\_bp\_model(bp\_model, X\_train, y\_train, X\_val, y\_val, epochs, batch\_size)  
 return bp\_model  
  
  
def evaluate\_final\_model(model, X\_test, y\_test):  
 performance\_metrics = evaluate\_model(model, X\_test, y\_test)  
 return performance\_metrics  
  
  
def calculate\_performance\_metrics(y\_true, y\_pred):  
 mse = mean\_squared\_error(y\_true, y\_pred)  
 mae = mean\_absolute\_error(y\_true, y\_pred)  
 r2 = r2\_score(y\_true, y\_pred)  
 return mse, mae, r2  
  
  
X\_train\_main, X\_val, y\_train\_main, y\_val = train\_test\_split(X\_train, y\_train, test\_size=0.2, random\_state=42)  
  
  
  
if \_\_name\_\_ == "\_\_main\_\_":  
 print("[\*]Training BP model")  
 bp\_model, history = train\_bp\_model(X\_train\_main, y\_train\_main, X\_val, y\_val)  
  
 print("[\*]Optimizing parameters using GA")  
 best\_individual = optimize\_parameters()  
  
 print("[\*]Integrating GA with BP model")  
 bp\_model, epochs, batch\_size = integrate\_ga\_with\_bp(best\_individual)  
  
 print("[\*]Training GA-BP model")  
 train\_ga\_bp\_model(bp\_model, X\_train\_main, y\_train\_main, X\_val, y\_val, epochs, batch\_size)  
  
 print("[\*]Performing cross-validation...")  
 avg\_metrics = cross\_validate(X\_scaled, y)  
 print(f"Cross-validation metrics: MSE={avg\_metrics[0]}, MAE={avg\_metrics[1]}, R2={avg\_metrics[2]}")  
  
 print("[\*]Evaluating the final model on test set...")  
 performance\_metrics = evaluate\_final\_model(bp\_model, X\_test, y\_test)  
 print(f"Test set performance metrics: MSE={performance\_metrics[0]}, MAE={performance\_metrics[1]}, R2={performance\_metrics[2]}")  
  
 print("[\*]Adjusting parameters based on validation set...")  
 bp\_model = adjust\_parameters(bp\_model, best\_individual, X\_train\_main, y\_train\_main, X\_val, y\_val)  
  
 print("[\*]Re-evaluating the final model on test set...")  
 performance\_metrics = evaluate\_final\_model(bp\_model, X\_test, y\_test)  
 print(f"Test set performance metrics (after adjustment): MSE={performance\_metrics[0]}, MAE={performance\_metrics[1]}, R2={performance\_metrics[2]}")  
  
 print("[\*]Saving Model...")  
 bp\_model.save("SDP\_GA-BP.h5")  
 bp\_model.save\_weights("weights.h5")  
  
 plt.plot(history.history['loss'], label='Training Loss')  
 plt.plot(history.history['val\_loss'], label='Validation Loss')  
 plt.xlabel('Epochs')  
 plt.ylabel('Loss')  
 plt.title('Learning Curves')  
 plt.legend()  
 plt.savefig('Learning\_Curves.png')  
 plt.show()  
  
 y\_pred = bp\_model.predict(X\_test)  
 plt.scatter(y\_test, y\_pred, label='Predictions')  
 plt.xlabel('Actual Values')  
 plt.ylabel('Predicted Values')  
 plt.title('Predicted vs Actual Values')  
 plt.legend()  
 plt.savefig('Predicted\_vs\_Actual\_Values.png')  
 plt.show()

**APPENDIX B: Performance Test Plots**

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