Concrete Slump, Flow, and Compressive Strength Prediction using Type-1 Fuzzy Rule-Based System (T1FRBS)

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1. Introduction

Concrete is a highly complex construction material, and its properties such as slump, slump flow, and compressive strength are influenced by various ingredients. Predicting these properties accurately is vital for quality control and optimal mix design. This project aims to develop a Type-1 Fuzzy Rule-Based System (T1FRBS) to predict the slump, slump flow, and 28-day compressive strength of concrete based on the proportions of its basic ingredients.

2. Methodology

This section details the approach used to develop the prediction system. The model is built upon a zero-order Takagi-Sugeno-Kang (TSK) fuzzy system, with rules derived using the Fuzzy C-Means (FCM) clustering algorithm. FCM is an unsupervised clustering technique that partitions data into fuzzy clusters, allowing each data point to belong to multiple clusters with varying membership degrees. This characteristic is particularly useful for modeling uncertainty and vagueness in real-world data. FCM minimizes an objective function that balances the distance between data points and cluster centers, weighted by the membership degrees. The resulting cluster centers define the antecedents of the fuzzy rules, while the membership values determine the rule firing strengths. The prediction system utilizes a zero-order Takagi-Sugeno-Kang (TSK) model where fuzzy rules are derived through the Fuzzy C-Means (FCM) clustering algorithm. The process is as follows:

2.1 Data Preprocessing

- **Dataset:** "concrete+slump+data.xlsx" with 103 data points.
- **Inputs:** Cement, Slag, Fly ash, Water, SP, Coarse Aggregate, Fine Aggregate.
- **Outputs:** SLUMP (cm), FLOW (cm), 28-day Compressive Strength (Mpa).
- Preprocessing includes handling missing values, removing duplicates, and normalizing input features.

2.2 Rule Extraction (FCMeans Class)

- The FCM algorithm clusters the input data into 'n' fuzzy clusters, where each cluster center forms the antecedent of a fuzzy rule.

- Membership degrees of data points to clusters determine the firing strengths of rules.
- Cluster centers are computed iteratively using the fuzzy partition matrix.

2.3 Fuzzy Set Derivation (T1FRBS Class)

Fuzzy set derivation is a crucial step in building the Type-1 Fuzzy Rule-Based System. In this project, Gaussian membership functions are used to model the fuzzy sets for each input variable, as they provide smooth transitions and are widely used for their mathematical convenience and interpretability.

The centers of these Gaussian functions correspond directly to the cluster centers obtained from the Fuzzy C-Means (FCM) algorithm. Each cluster center represents the peak of a membership function, capturing the most representative value of a fuzzy set.

The standard deviations (sigma) of the Gaussian functions are derived from the range of input features. Specifically, sigma is computed by dividing the range of each input variable (max - min) by twice the number of clusters, ensuring adequate overlap between fuzzy sets to handle uncertainty and provide smooth interpolation between rules.

This fuzzy set derivation enables the system to translate crisp input values into fuzzy membership degrees, which are essential for rule activation and subsequent prediction steps.

2.4 Consequent Parameter Identification

- Each fuzzy rule has a zero-order TSK consequent (a constant value 'p').
- Parameters are determined by weighted least squares using the membership degrees.

2.5 Prediction

- Predictions are made by computing the weighted average of all rule consequents, weighted by their firing strengths.

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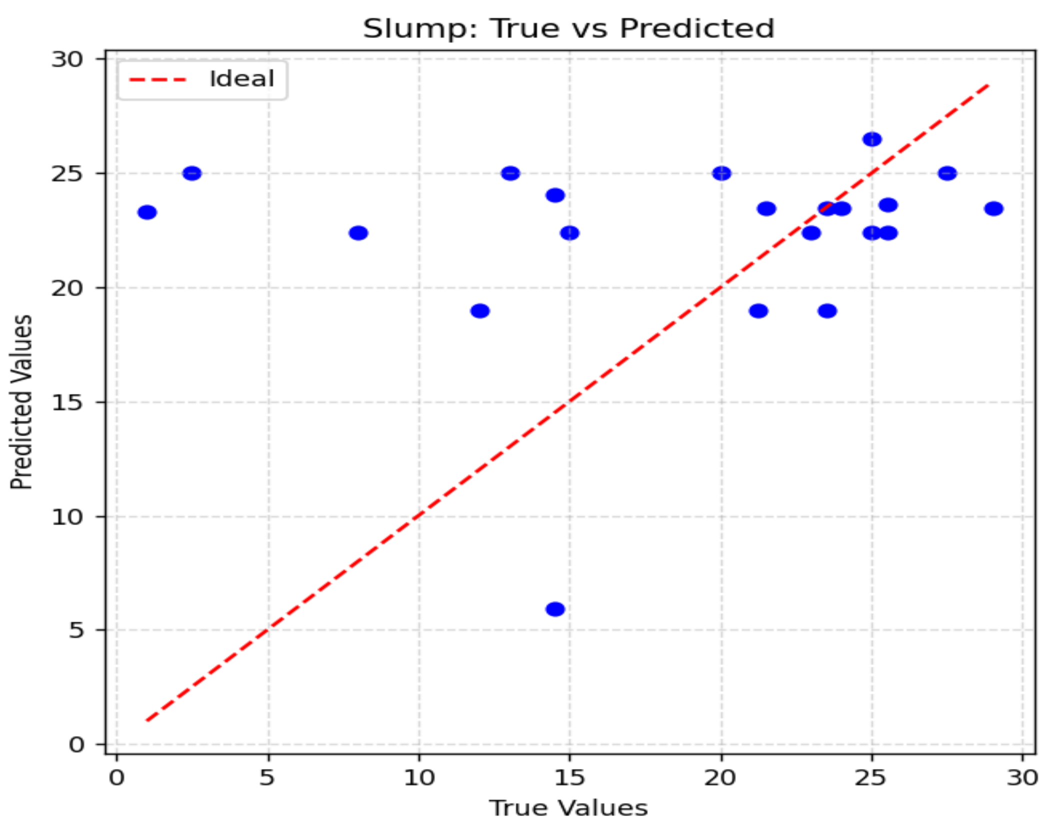
3. Obtained Results

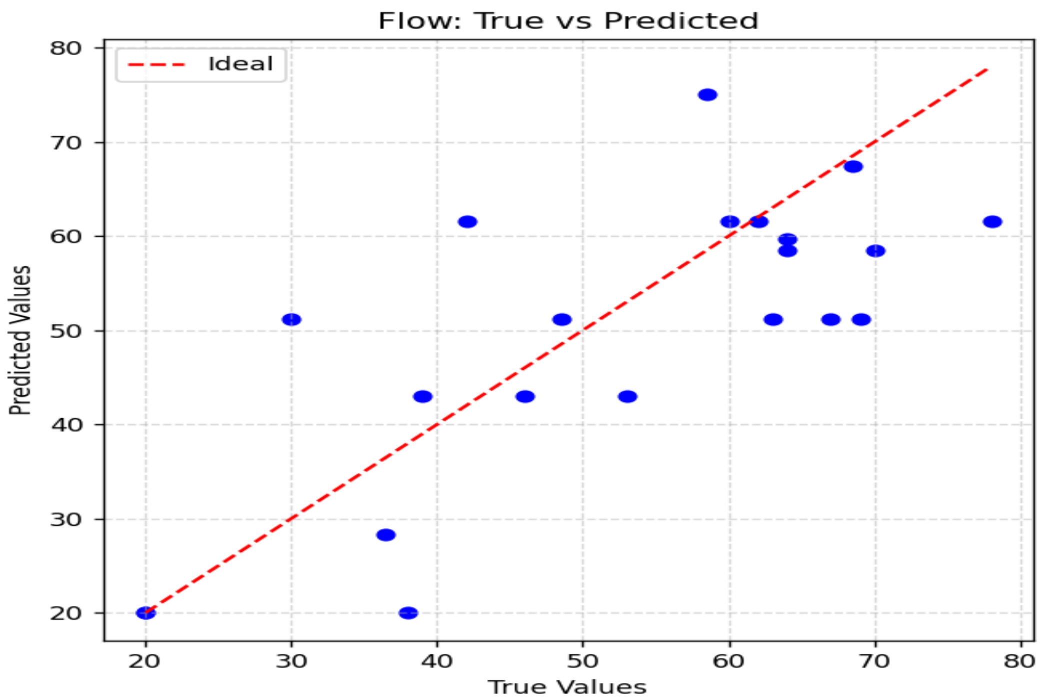
The results include three plots illustrating the derived fuzzy rules for each output variable: slump_rules, flow_rules, and compressive_strength_rules. These plots visualize the membership functions and how they define the rule antecedents for each prediction task. The model was trained and tested over 50 random splits (80% training, 20% testing). The results are summarized below: model was trained and tested over 50 random splits (80% training, 20% testing). The results are summarized below:

Output Variable	**Mean RMSE**	**Best RMSE**
SLUMP (cm)	**8.6494**	**4.9408**
FLOW (cm)	**17.2342**	**11.3616**
Compressive Strength (Mpa)	**6.6607**	**4.7337**

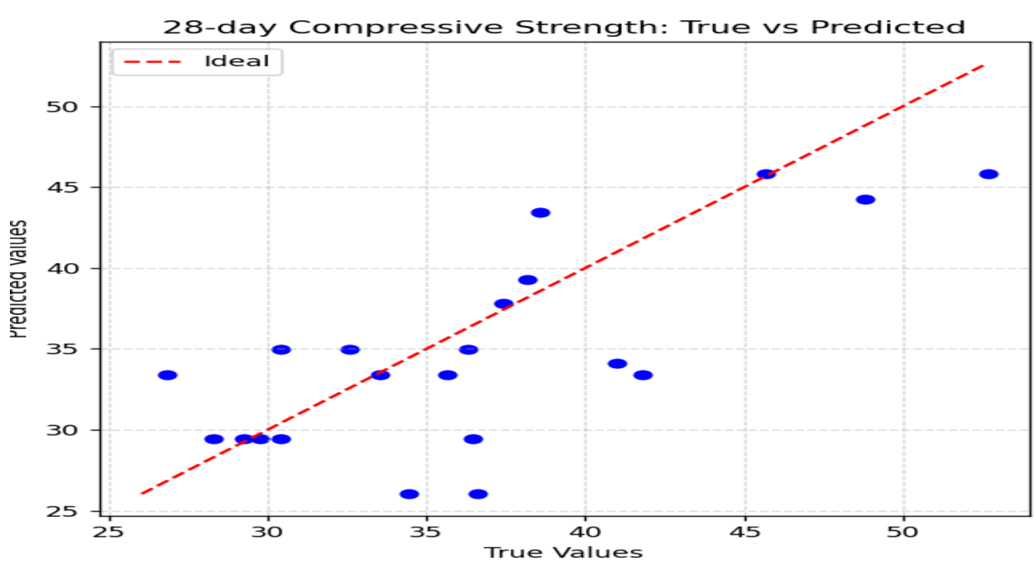
• **Figure 1:** slump true and predicted



• **Figure 2:** Flow true and predicted



• **Figure 3:** compressive_strength true and predicted



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4. Appendix

4.2 How to Run the Project

1. Ensure Python and required libraries (numpy, pandas, matplotlib, openpyxl) are installed.
2. Place "concrete+slump+data.xlsx" in the project directory.
3. Run the code using:

   python slumpp.py

4. The console will display RMSE results, and plots will be saved as PNG files.

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5. Project Components Overview

5.1 FCMeans Class

- **Purpose:** Performs Fuzzy C-Means clustering.
- **Functions:**
  - **__init__:** Initializes parameters.
  - **fit:** Computes cluster centers and membership matrix iteratively.

Mathematical Formulation:

Cluster centers are updated as:

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m}$$

Membership matrix update:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{||x_j - c_i||}{||x_j - c_k||} \right)^{2/(m-1)}}$$

5.2 T1FRBS Class

- **Purpose:** Implements the Type-1 Fuzzy Rule-Based System.
- **Functions:**
    - **__init__:** Initializes rule count, features, and parameters.
    - **compute_membership:** Calculates Gaussian membership values.
    - **fit:** Trains the model and derives consequent parameters.
    - **predict:** Predicts a single data point.
    - **predict_all:** Predicts multiple data points.
    - **plot_rules:** Visualizes membership functions.

Gaussian Membership Function:

$$\mu(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right)$$

Prediction Formulation:

$$\hat{y} = \frac{\sum_{i=1}^{n_{rules}} \mu_i(x) p_i}{\sum_{i=1}^{n_{rules}} \mu_i(x)}$$

5.3 Utility Functions

- **normalizer:** Normalizes input features.
- **rmse:** Computes Root Mean Squared Error.
- **plot_predictions:** Plots predicted vs. true values.

RMSE Formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

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6. Conclusion

This project successfully implemented a Type-1 Fuzzy Rule-Based System to predict key concrete properties. The T1FRBS model demonstrates reliable performance across multiple runs, providing an interpretable and effective approach to modeling complex relationships in concrete mix designs.