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Wind power forecasting model based on linguistic fuzzy rules

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ABSTRACT

The design and operationalization of a wind energy system is mainly based on wind speed and wind direction, theses parameters depend on several geographic, temporal, and climatic factors. Fluctuating factors such as climate cause irregularities in wind energy production. Therefore, wind power forecasting is necessary before using wind power systems. Furthermore, in order to make informed decisions, it is necessary to explain the system's predictions to stakeholders. The explainable artificial intelligence (XAI) provides an interactive interface for intelligent systems to interact with machines, validate their results, and trust their behavior. In this paper, we provide an interpretable system for predicting wind energy using weather data. This system is based on a two-step method for fuzzy rules learning clustering (FRLC). The first step uses subtractive clustering and a linguistic approximation to extract linguistic rules. The second step uses linguistic hedges to refine linguistic rules. FRLC is compared to with artificial neural network (ANN), random forest (RF), k-nearest neighbors (K-NN), and support vector regression (SVR) models. The experimental results show that the accuracy of FRLC is acceptable regarding the comparison models and outperform them in terms of the interpretability. In parallel with prediction, FRLC model provides a set of linguistic fuzzy rules that explain the obtained results to the stakeholders.

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1. INTRODUCTION

Countries, governments, and energy-producing companies are concerned with renewable energy sources due to their low cost and environmental conservation. Wind energy is one of the most important sources of renewable energy, characterized by sustainability and ability to produce energy throughout the day [1], and is also practical for systems that require uninterrupted energy. It is also possible to calculate the amounts of energy to be generated by being able to predict the seasonal variations of the wind in the short, medium, and long term. It should be noted that wind turbines can be installed on existing farms without loss of agricultural area, but the use of wind energy remains a major challenge, on the one hand, the initial investment costs are generally higher than conventional energy stations. On the other hand, reliable studies must be carried out in a promising area, these areas which are often remote areas generate a high cost linked to the transport of equipment and machines, as well as the connection of these areas to the national lines transmission systems. Finally, wind turbines cause environmental damage such as vibrations, noise, and sometimes aesthetic pollution.

Machine learning is a branch of computer science that allows computers to learn from previous data [2]. In general, machine learning algorithms are used to describe the behavior of the dataset and the relationships between the inputs and the outputs. As a result, machine learning is one of the alternatives for predicting wind power based on wind speed data.

Wind energy forecasts are classified into three types: long-term, medium-term, and short-term forecasts. Long-term forecasts range from two to seven days, this type enables manufacturing chain decisions and maintenance schedules to be followed in order to reduce operating costs. The medium-term prediction ranges from six to twenty-four hours, ensuring operational stability in the electricity market. The short-term prediction ranges from 30 minutes to 6 hours and is used to balance supply and demand on the electricity market [3].

In the literature, there are three types of wind energy forecast models: physical, statistical, and hybrid models. The physical model takes into account both the structure of the wind power architecture and the numerical prediction data, whereas the statistical model is based on meteorological data, and the hybrid model combines the two [4]. The prediction model typically consists of two main steps: data pre-processing and prediction. Data pre-processing step aims to reduce the number of forecast errors and operations by sampling and analyzing data, as well as the estimate and measurement time. In the prediction step, two main methods are used: statistical and intelligent methods. Statistical methods are based on time series and regression methods, for example: non-linear regression and integrated moving average auto regression [5]. There are a variety of artificial intelligence (AI) methods, including the artificial fuzzy neural inference system [6], the artificial neural network (ANN) [7] and the fuzzy expert system [8]. Each method is characterized by their advantages and disadvantages, and no method can provide the best results for all data. Statistical methods look for possible relationships between inputs and outputs, those methods give remarkable interpretability but often poor precision. Although AI methods use black and gray boxes, they offer often precise results, but limited interpretations [9]. Furthermore, in order to make informed decisions, it is necessary to explain the system's predictions to the stakeholders [10]. In order to deal with these problems, it is important to apply XAI explanatory techniques to opaque models such as (SHAP, LIME, CONTRAFACTUAL, and ANCRE) [11]; or building an interpretable model with a good balance between accuracy and interpretability [12].

In this paper, we propose an interpretable model to forecast one hour ahead of wind power based on subtractive clustering and linguistic hedges, it is called: fuzzy rule learning through clustering (FRLC). FRLC uses local time and two meteorological parameters: wind speed and wind direction. To evaluate the system's efficiency, the study compares FRLC model with ANN, random forest (RF), k-nearest neighbors (K-NN), and support vector regression (SVR) models. The next section presents the related works. Section 3 describes the fuzzy rules-based system. Section 4 explains the proposed method by presenting the dataset and the performance evaluation methods utilized in this study. Section 5 presents the proposed method. Section 6 shows experiments development and obtained results.

2. RELATED WORK

One of the most important wind farms is Sotavento, which has an important database for generating wind energy. This data was the subject of many research and studies that focused on forecasting the amount of wind energy to be produced in the short, medium, and long term. Table 1 shows the relevant research using this data. In this context, Misha and Dash [13] have proposed an accurate model for wind power prediction on a short-term, using a low-complexity pseudo-inverse legendre neural network (PILNNR) with radial basis function (RBF) units in the hidden layer. D-Vico *et al.* [14] also have used deep neural structures (DNNs) to predict wind energy, with inputs derived from digital weather forecasting systems. Bagheri *et al*. [15] have developed a new approach to predicting wind energy based on empirical mode decomposition (EMD), a selection feature and a forecast engine, where the engine used a hybrid method based on AI. Despite the fact that Wang *et al.* [16] created a deep belief network (DBN) model for wind power forecasting based on numerical weather prediction (NWP), the k-means clustering technique was added to this model to deal with NWP data. To improve the output of the model, a large number of NWP samples are selected as the input via clustering analysis. Çevik *et al*. [17] prefers EMD and stationary wavelet decomposition (SWD) in the preprocessing step of. The researchers used the artificial neuro-fuzzy inference system (ANFIS), ANNs, and SVR in the forecasting process to predict wind speed, wind direction, and wind power from the dataset.

Table 1. The most important studies using Sotavento data

Study	[13]	[14]	[15]	[16]	[17]
Year	2017	2017	2018	2018	2019
Pre-processing			EMD	k-means clustering	SWD
Method	PIRBFNN-FF	DNNs	HBMO	DBN	ANFIS
Compared Method		SVR	ARMAX, RBF, MLP	BP and MWNN	SVR -ANN
Forecast rang	Next hour	Next 3 h	1 h	10 min	48 h
Data	Wind speed, wind power	NWP (pressure, temperature, wind speed and wind direction)		NWP (wind speed, wind direction, temperature, humidity, pressure)	Wind speed, wind power, Wind direction
Data range	2016	2011–2013	2015	2016	2005-2007 2010-2012
Train data	1,800 h	1 year	48 weeks	324 days	4 years
Test data	1,600 h	1 year	4 weeks	36 days	2 years
Error criteria	RMSE	MAE	NRMSE	NMAE and NRMSE	MAE
Error	Between 0.98 and 1.85	7.53	5.45	Between 0.0236 and 0.0322	Between 0.333, 0.294 and 0.278

pseudo-inverse legendre neural network and adaptive firefly algorithm; (PIRBFNN-FF), honey bee mating optimization (HBMO); autoregressive moving average exogenous (ARMAX); multi-layer perception neural network (MLP); back propagation (BP) neural network; morlet wavelet neural network (MWNN).

3. FUZZY RULES BASED SYSTEM

The fuzzy rules based system (FRBS) is a method by which data from an organization is mapped into outgoing data using the fuzzy logic. The FRBS consists of a knowledge base (KB), a fuzzification interface that converts crisp values into fuzzy sets, an inference engine that uses them to define other fuzzy sets, and a defuzzification interface that translates the resulting fuzzy sets into a crisp value. The KB consists of a rulebase (RB) and a database (DB). The RB is a set of fuzzy if-then rules and the DB is a set of linguistic variables, in which, each linguistic label and their meaning are defined. In the literature, there are two kinds of FRBSs: MAMDANI FRBS (or linguistic FRBS) [18] and Takagi–Sugeno–Kang (TSK) FRBS [19]. Figure 1 shows the MAMDANI FRBS approach; the fuzzy sets represent the consequents and the antecedents. The consequence is a weighted combination of input variables with fuzzy sets representing the antecedents of the TSK FRBS approach. Two criteria are used for evaluating FRBSs, which are accuracy and interpretability. The accuracy is typically measured with the root mean square error (RMSE). There are two types of interpretability [20], [21]: the complexity and the semantics. Figure 2 illustrates the interpretability in DB and in RB. The complexity-based interpretability is designed to reduce the complexity of the obtained system, which normally is measured with the number of rules in RB, the number of antecedents per rule and the number of linguistic labels for each linguistic variable. On the other side, the semantics-based interpretability is designed to preserve the semantics in KB, which normally imposes restrictions on the membership functions in DB to preserving the meaning of the linguistic labels, these restrictions concern the distinguishability, the coverage, the fuzzy ordering, the normalization. In the RB, the semantics-based interpretability requires certain constraints such as: the consistency of rules, the number of rules fired simultaneously and the transparency of rule structure. Thus, for a good accuracy-interpretability balance in FRBSs, three requirements are necessary: The accuracy, the complexity, and the semantic interpretability.

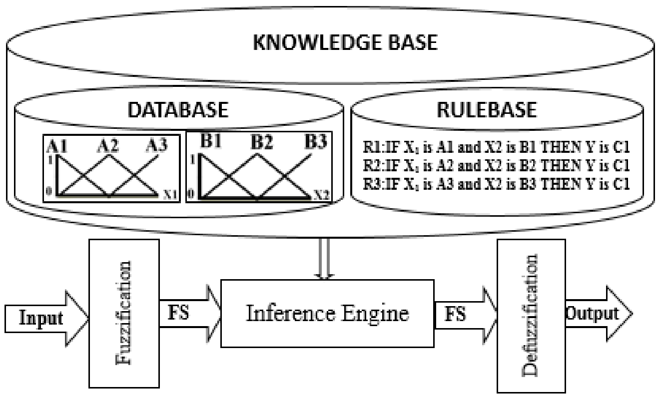

Figure 1. FRBS model

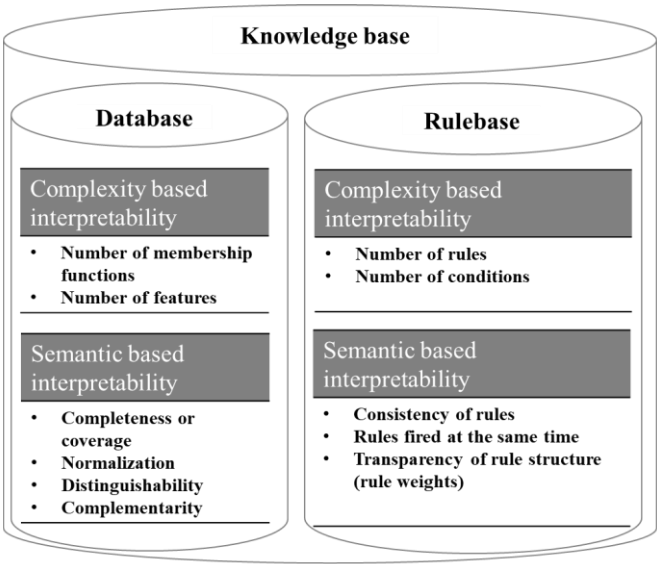

Figure 2. Interpretability indexes of FRBS

4. MATERIALS AND METHOD

4.1. Data description and preprocessing

In this study, the used data is from Sotavento Galicia wind farm, which is situated in Galicia, Northwestern Spain (43.354 ◦N Latitude and 7.881 ◦W) [22], Sotavento is a research and development center which was established in 2001. This wind farm has 24 wind turbines with five different technologies and nine machine models. Every 10 min, the anemometric tower measures and records the wind speed, wind power and wind direction [23], then the record data are sent to the wind farm website with 10 min, hourly and daily basis. The considered period is between 2011 to 2012 with 17,342 instances, this period provides data which includes measurements of wind speed and wind direction taken on an hourly basis.

4.2. Statistical indicator preprocessing

The performance of the models developed is evaluated by applying the metrics indicators. In this study two metric indicators are adopted: the mean absolute error (MAE) and the RMSE. The MAE measures the proximity of the predicted values to the observed values, the RMSE is used to measure the level of scattering in the obtained models. In (1) and (2), respectively, define the MAE and the RMSE where n denotes the number of data, Y_i represents the predicted value and X_i represents the observed value.

$$MAE = \frac{1}{n} \quad \sum_{i=1}^{n} |X_i - Y_i|) \tag{1}$$

$$MSE = \sqrt{\frac{1}{n} \quad \sum_{i=1}^{n} (X_i - Y_i)^{\,2}} \tag{2}$$

5. FUZZY RULE LEARNING THROUGHT CLUSTRING

This contribution's goal is to provide a FRBS wind power forecast with a reasonable accuracy-interpretability trade-off. The approach is described in [9] and it is an automated development of linguistic FRBS models from data in which researchers incorporate an embedded DB learning enveloping RB learning. The architecture of FRLC is seen in Figure 3. Using the gaussian membership functions, uniform discretization is used to establish the fuzzy partitions of the linguistic variables (the number of linguistic labels) and to describe the meaning of each linguistic label [24]. Subtractive clustering and linguistic hedges underpin RB learning. Subtractive clustering is a type of fuzzy clustering based on data point density [25], [26].

Consider a set of N data points $\{x_1, x_2, \ldots, x_N\}$ in an M-dimensional space. Using (3), the subtractive clustering method estimates the potential of a data point x_i (3).

$$P_i = \sum_{j=1}^{N} e^{-\alpha \|x_i - x_j\|^2} \tag{3}$$

where $\alpha=4/r_a^2$ and r_a are the cluster radius, and it is an M-dimensional vector of positive scalars specifying the radius value in each dimension. The subtractive clustering technique starts with four parameters: the cluster radius r_a, the accept ratio ($\acute{\varepsilon}$=0.5), the reject ratio (ε=0.15), and the cluster neighborhood (r_b=1.25*r_a). As shown in Figure 3, the radius module computes the radius r_a using the DB parameters [9]. Let $\{var_1,var_2,..., var_M\}$be the set of linguistic variables, and $min(var_i)$ and $max(var_i)$ be the minimum and maximum values of var_i's universe of discourse, respectively. Let $\{MFun_j^k$ / $k=1... l_j\}$ be the set of Gaussian membership functions produced by uniform discretization of varj, with the $MFun_j^k$ parameters being its mean C_j^k and standard deviation σ_j^k. With (4), the module computes the j^{th} value r_d^j of r_a.

$$r_a^j = \frac{\sigma_{j^k}\sqrt{8}}{(max(var_j)-min(var_j))} \tag{4}$$

The default values of r_b, $\acute{\varepsilon}$ and ε have been tested to see how they effect the number of extracted clusters. Indeed, constant starting parameter values might result in an excessive or inadequate number of clusters. As a result, these values must be adapted to numerical data points. The authors offer an adaptive subtractive clustering in which the user does not specify the values of r_b and ε. r_b belongs to the set $Sr_b=\{r_a*(1+f/10) / f=1...7\}$ in adaptive subtractive clustering, which is used to define the good neighborhood of retrieved clusters. ε value is computed using maximal and minimal potential (P_{max} and P_{min}):$\varepsilon=P_{min}/P_{max}$. In experiments, $\acute{\varepsilon}=0.5$ is a suitable ratio for accepting clusters. The rule module projects extracted clusters in all dimensions to create linguistic fuzzy rules, which gives a collection of fuzzy rules. Following that, the module uses Hamming distance to linguistically approximate the fuzzy rule with Euclidean distance and increase the accuracy using language hedges (very, plus, minus, more or less, slightly, and a little) [27]. The linguistic approximation of the fuzzy rules is illustrated in (5):

$$T_i^{\ j} \leftarrow \underset{k=1,\dots,\ l_j}{argmin} \left(\left|x_{ij}^{\ *} - C_j^{\ k}\right|\right) \tag{5}$$

With x_{ij}^* is the j^{th} value of x_i^* and C_j^k the mean of $MFun_j^k$. To improve the accuracy, (6) calculates the Hamming distance between $AFun_i^j$ and all $(MFun_{ij}^*)^P$:

$$D_h = \int_{min(v_j)}^{max(v_j)} |AFun_i^j(x) - (MFun_{ij}^*)^P(x)|\, dx \tag{6}$$

where P denotes the linguistic hedge parameter and $AFun_i^j$ is the MF of cluster x_i^* in j^{th} dimension. In a MAMDANI FRBS, the evaluation module evaluates the obtained KB. Each linguistic fuzzy rule in the RB comprises M-1 conditions. To simplify the RB while improving accuracy, researchers decreased the number of conditions with *don't care* condition [20]. Details the FRLC training algorithm [9].

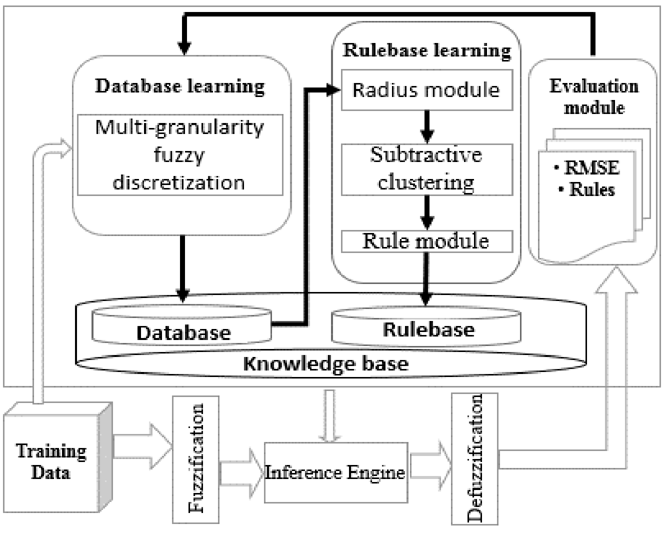

Figure 3. FRLC architecture

6. RESULTS AND DISCUSSION

To analyze the efficiency of FRLC, researchers dealt with prediction of solar radiation in Galicia located on northwestern Spain (43.354 ◦N Latitude and 7.881 ◦W). The obtained results are compared with ANN, RF, K-NN, and SVR models. Table 2 lists the tuned parameters, with their meanings.

Table 2. Comparison algorithms and their tuned parameters

Algorithms	Parameters
SVR	Gamma ∈ {‘scale’, ‘auto’}
	Kernel ∈ {'rbf','linear'}
RF	n_estimators ∈ { 10, 20, 30, 40, 50, 60, 70, 80, 90, 100}
K-NN	K ∈ {1,2, …,30}
	Weights ∈ {'uniform','distance'}
ANN	hidden_layer_sizes ∈ { 4,8,16}
	activation ∈ {'tanh','relu'}
	solver ∈ {'sgd','adam'}
	learning rate ∈ {0.001,0.01,0.1}

'rbf': RBF; 'linear': linear; 'uniform': uniform weights; 'distance': inverse distance weighting; 'tanh': hyperbolic tan function; 'relu': rectified linear unit function; 'sgd': stochastic gradient descent method; 'adam': stochastic gradient-based optimization method

6.1. Results of 10-fold cross-validation for algorithms performance

Table 3 shows the results of five algorithms after their initial parameters were optimized. RF algorithm outperforms the other five algorithms with RMSE=902 and MAE=595. A poor performance was observed for ANN algorithm with RMSE=1255 and MAE=860. FRLC algorithm has RMSE=1247 and MAE=649. These results show the competitiveness of FRLC algorithm in wind forecasting.

Table 3. Comparison of the developed models

Models	Parameters	RMSE	MAE
ANN	– hidden_layer_sizes=8 – activation ='relu' – solver='adam' – learning rate=0.1	1,255	860
SVR	– gamma= 'auto' – kernel='linear'	1,501	1,224
FRLC	– NBrulesMax=15	1,247	934
K-NN	– n_neighbors'=8 – weights='uniform'	966	649
RF	– max_features= 'sqrt' – n_estimators=90	902	595

6.2. Explainability of the FRLC model

From the explainability point of view, although transparency of K-NN algorithm, K-NN does not provides enough explanation to the end user. In the case of SVM, ANN and RF algorithms, post-explanation techniques such as model-independent techniques (lime, shape, contrafactuals) and model-specific techniques like INTREES [28] are required. Each technique provides partial explanations. Therefore, it is necessary to combine these methods to answer user questions. This requires additional effort in order to generate more refined explanations and debug the model in question. On the other hand, FRLC algorithm provides a simple and transparent linguistic KB in which all the input variables are discretized into uniform fuzzy partition. Figure 4 presents the linguistic DB of FRLC with 9,3,9 membership functions for wind speed, wind direction and wind power linguistic variables, respectively. The RB of FRLC contains five linguistic rules:

R1: if WS is more or less MF2 Then WP is MF1
R2: if WS is MF4 and WD is MF2 Then WP is MF5
R3: if WS is more or less MF1 Then WP is MF1
R4: if WS is more or less MF6 Then WP is MF7
R5: if WS is more or less MF3 Then WP is MF1

Figure 5 shows the first linguistic fuzzy rule generated in RB (R1). Domain experts can use fuzzy linguistic rules to analyze, criticize, accept, or reject the results provided by FRLC.

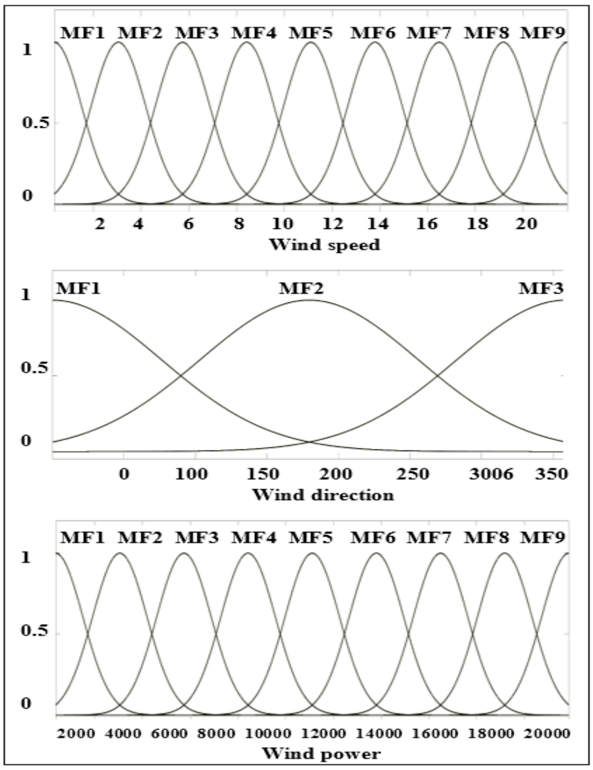

Figure 4. The membership functions for wind speed, wind direction, and wind power linguistic variables

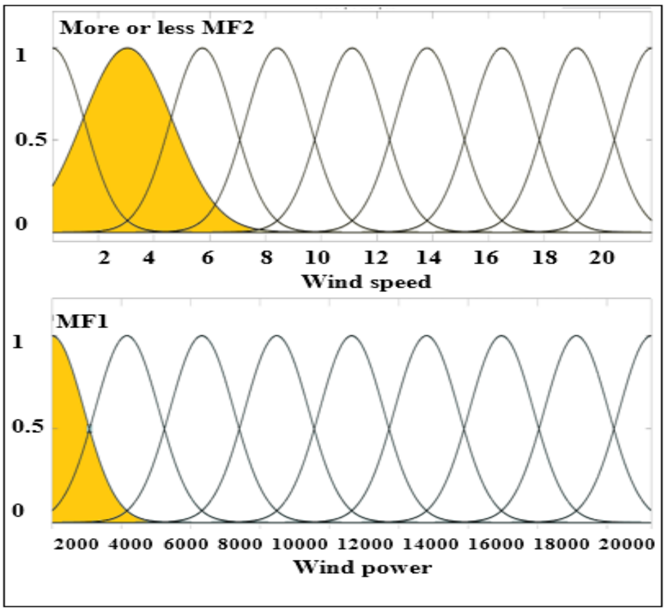

Figure 5. The first linguistic rule in RB

7. CONCLUSION

Wind power is a free, big and renewable source of energy. In this paper, a new fuzzy rule-based system called "FRLC"is presented. In fact, FRLC based on adaptive subtractive clustering and linguistic hedges was compared to ANN, RF, K-NN, and SVR models. The results indicate the competitivity of the proposed approach in term of accuracy and interpretability. Furthermore, FRLC provides a good balance between interpretability and accuracy of wind energy forecast. The current effort seeks to increase the

FRLC's accuracy and scalability, as well as to provide interactive natural language interfaces and visual explanations.

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