collection stations, a dirty, real-world dataset obtained from a single, commercially available, solar-powered weather collection station is used. If it can be shown that DFFNN is trained from this dataset are capable of predicting even a few useful variables with reasonable accuracy, then further research into predicting a wider range of regression and classification variables from the dataset is warranted.

II. BACKGROUND STUDY

In [5] a Feed forward multi-layered artificial neural network model is designed to estimate the maximum surface temperature and relative humidity needed for the genesis of severe thunderstorms over Calcutta. Using single layer network and one hidden layer artificial neural network prediction error is calculated and compared. Result shows the efficiency of the one hidden layer ANN. This estimation can help in predicting a probable thunderstorm day with one day or 24 hrs in advance. In [6] described a weather forecasting problem-rain fall using different neural network architectures namely Electronic Neural Network (ENN) model and optoelectronic neural network model. They did experiments using these two models and the percentage of correctness of the rainfall estimation of the neural network models and the meteorological experts are compared. The accuracy of ENN and opto-electronic neural network models, is compared with two metrological experts.

In [7] shows, how ANN can be used for Forecasting Weather for Iran city. They implements ANN for one day ahead prediction of weather parameter i.e. temperature of Iran. Their study was based on most common neural network model Multilayer Perceptron (MLP) which is trained and tested using ten years past metrological data. Minimum error is achieved using MLP between exact and predicted values at each day and has a good performance, reasonable prediction accuracy and minimum prediction error in general.

In [8] a new technique is proposed for Weather classification and forecasting using Levenberg Marquardt Back Propagation Feed Forward Neural Network. Levenberg BP is the fastest and best among many BP. The classification and Prediction of Weather using BPNN is basically a forecasting kit which aims to gather data i.e. weather parameters like temperature, pressure, humidity, wind direction. These predictors are taken as input neuron to BP. In [10] the past data like rainfall, wind speed, dew point, and temperature is used to predict weather using k nearest neighbor algorithm. It generates accurate result in advance in prediction of weather. The results are in Boolean attributes and numeric values. The changes can be recognized by using the patterns. Pattern recognition can be used.

In [11] data mining techniques used meteorological data for prediction and decision making. The Weather forecasting parameter's relationships are found using data mining techniques. Since meteorological data are vast and time constrained, it not only need to modify by traditional data mining. But also can be modified using some other techniques. In [12] by using decision trees the stored data in past are used to predict the upcoming climate. By using all parameters the prediction can be improved and perfect. And also the limit for prediction will not limit itself. In [13] self organizing data mining technique called enhanced Group Method of Data Handling (e-GMDH) is employed to predict and forecast weather. e- GMDH works efficiently when compared with older data mining techniques. Graphical User Interface (GUI) which is partly placed in the algorithm must be updated to include the current functionalities.

First, many experiments have used with neural networks to predict quantitative rainfall amounts at various locations and look-ahead ranges. For instance, researchers in Thailand were obtained highly accurate forecasts to predict quantitative rainfall amounts in the one to three hour look-ahead range using feed-forward neural networks in order to predict possible flooding dangers [14]. Additionally, neural networks have been used in research to generate probabilities of precipitation and quantitative precipitation forecasts using data from the Eta atmospheric model and

upper air soundings. As shown next, neural networks have also been used to predict other less common weather phenomena. Neural networks have also been used to predict weather phenomena besides the traditional forecast values, such as probability/amount of rainfall, wind speed, barometric pressure, etc. Tornadoes are predicted successfully[15]. Identification of fog at various forecast ranges ranging from 3 hours to 18 hours around Canberra International Airport [15], Australia. Hopefully, this survey provides in depth idea of the depth and variety of neural network-based weather forecasting.

III. PROPOSED DEEP FEED FORWARD NEURAL NETWORK METHODOLOGY AND FUZZY METHODS FOR DATA PREPROCESSING

The goal of weather prediction is to determine the feasibility of using a rather imperfect dataset obtained from a single collection unit as input to neural networks in order to obtain regression and Deep Forward Neural Network (DFFNN) and Artificial Neural Network (ANN) classification predictions methods for various weather variables of interest. The variables defining weather conditions like temperature (maximum or minimum), relative humidity, pressure etc., vary continuously with time, forming time series of each parameter and can be used to develop a forecasting model either statistically or using some other classification methods . This research is distinguished from existing ANN research primarily through the choice of datasets. Rather than using large datasets built over decades from a network of collection stations, a dirty, real-world dataset obtained from a single, commercially available, solar-powered weather collection station is used. If it can be shown that DFFNN is trained from this dataset are capable of predicting even a few useful variables with reasonable accuracy, then further research into predicting a wider range of regression and classification variables from the dataset is warranted.

The practical applications of a system make this research worthwhile. First, the experiment uses low-cost or free software and hardware, which minimizes the production cost of a system built around the DFFNN model. Second, let's assume that experimentation reveals that it is possible to develop a regression and classification model with strong predictive capabilities from the source dataset through the use of neural networks. If a collection station is then prepositioned in a crop field and allowed to gather data over time, then a neural network can be trained to predict weather variables of interest for that small geographical point. This information would be very useful in remote areas, where radio and network connectivity to existing weather services is limited. In addition the proposed work, outliers in the dataset is also removed by using fuzzy technique during the preprocessing task.

Incomplete dataset samples are removed by data preprocessing is a common step in many disciplines, including data mining, data warehousing, and optimization problems. As this section explains, data preprocessing also plays a very important role in neural networking. First, data normalization is examined by using the fuzzy technique. Data normalizing is the process of scaling data "to fall within a smaller range, such as -1.0 to 1.0, or 0.0 to 1.0" [19]. To perform the scaling task in this work data normalization is carreiedout using fuzzy technique which converts the original dataset samples into fuzzified values 0-1. Fuzzy systems are created using membership functions (MFs) which is modeled based on dataset. Therefore, there is relation between uncertainty of input data and fuzziness expressed by MFs. Outliers and noisy data are kinds of uncertainty which doesn't affect on membership function.

Data normalization is used to remove the dependence on measurement units using fuzzy technique, which is directly relevant to weather forecasting since predictor variables are measured using a wide variety of units (miles per hour, degrees Fahrenheit, inches of Mercury, etc.). Data normalization using fuzzy technique has direct implications to neural network performance. In fact, "normalizing the input values for each attribute measured in the training tuples will help speed up the learning phase" [18].

Furthermore, it is important to normalize Neural Network training data in order to prevent weights. Next, the issue of missing values in training data is explored.

Real world data won't be a perfect one because of noisy and missing values. Data mining research has produced several methods of dealing with such dirty data, including interpolation of missing values, binning, clustering for outlier analysis, etc [18]. In the context of neural network-based weather prediction systems however, research has established that removing training tuples with missing values is usually the wisest approach. The forecasting skill of a neural network trained using replacement values for missing values is at the mercy of the quality of the estimated values [19]. In other words, if the estimated values are highly inaccurate, then the predictive capability of a neural network trained with this data will suffer. Furthermore, by comparing Neural Networks trained using tuples with estimated values and neural networks trained using only complete data, researchers found that there was no significant benefit to using estimated values in training tuples [19].

Deep Feed Forward Neural Network (DFFNN)

A DFNN is a feed-forward, artificial neural network that has more than one layer of hidden units between its inputs and its outputs. Each hidden unit, *j*, typically uses the logistic function (the closely related hyberbolic tangent is also often used and any function with a well-behaved derivative can be used) to map its total input from the layer below, x_j, to the scalar state, y_j that it sends to the layer above.

$$y_j = logistic(x_j) = \frac{1}{1+e^{-x_j}} \quad (1)$$

$$x_j = b_j + \sum_i y_i w_{ij} \quad (2)$$

where b_j is the j^{th} unit bias, i is an layer index, and w_{ij} is the weight on a connection to unit j from unit i in the layer below. For multiclass classification, output unit j converts its total input weather prediction preprocessed dataset samples into x_j and into a class probability, p_j , by using the "softmax" nonlinearity

$$p_j = \frac{\exp(x_j)}{\sum_k \exp(x_k)} \quad (3)$$

where k is an class index. DNNs can be Discriminatively Trained (DT) by backpropagating derivatives with cost function that measures the discrepancy between the target outputs and the actual outputs produced for each training case [14]. The natural cost function C is the cross entropy between the target probabilities d and the outputs of the softmax, p

$$C = -\sum_j d_j \log p_j \quad (4)$$

where the target probabilities will be one or zero, that are the supervised information provided to train the DNN classifier. For large training sets, it is typically more efficient to compute the derivatives on a small, random "minibatch" of training cases, rather than the whole training set, before updating the weights in proportion to the gradient. This stochastic gradient descent method can be further improved by using a "momentum" coefficient, which has the value $0 < \alpha < 1$, that smooths the gradient computed for minibatch t, thereby damping oscillations across ravines and speeding progress down ravines. The bias update rule can be derived by treating them as weights on connections coming from units that always have a state of one.

$$\Delta w_{ij}(t) = \alpha \Delta w_{ij}(t-1) - \in \frac{\partial C}{\partial w_{ij}(t)} \quad (5)$$

Overfitting is reduced by large weights that can be penalized in proportion to their squared magnitude, or the learning can simply be terminated at the point at which performance on a held-out validation set starts getting worse [20]. In DNNs with full connectivity between adjacent layers, the initial weights are given small random values to prevent all of the hidden units in a layer from

getting exactly the same gradient.

It is very difficult to optimize DNNs with many hidden layers. Gradient descent from a random starting point near the origin is not the best way to find a good weights, and unless the initial scales of the weights are carefully chosen [20]. The backpropagated gradients will have very different magnitudes in different layers. In addition to the optimization issues, DNNs may generalize poorly to held-out test data. DNNs with many hidden layers and many units per layer are very flexible models with a very large number of parameters. Very complex and highly nonlinear relationships between inputs and outputs are made. This ability is important for high quality weather prediction, but it also allows them to model spurious regularities that are an accidental property of the particular examples in the training set, which will cause overfitting. The overfitting is reduced by weight penalties or early stopping.

There are many ways to determine the number of hidden neurons. In this experiment, a specific forecast from a specific dataset is viewed as a distinct neural network problem. For instance, across all datasets, a distinct set of neural networks was trained to predict minimum temperature at the 1-hour lookahead range, while a different distinct set of neural networks was trained to predict minimum temperature at the 3-hour look-ahead range. This process was repeated for each look-ahead forecast in every dataset. The combination of partitioning each forecast problem into a set of neural network problems and performing 10-fold cross validation for each Neural Network in each set made it unfeasible to adopt a trial and error method to determine the optimum number of hidden layers and hidden layer neurons. The trial an d error method seems more appropriate for fine-tuning a neural network used for a specific forecasting problem, such as determining the optimum neural network structure for predicting maximum gust values at the 12-hour look-ahead range from the 1-hour dataset. In order to generate a variety of neural network topologies, this experiment used an approach based off the number of inputs and outputs in the given forecasting problem. An existing strategy suggests that the number of hidden layer neurons should be in the range $[2^{\frac{n}{2}}, 2n + m]$, where n is the number of input neurons and m is the number of output neurons [14]. This suggestion formed the basis for topology generation in this experiment.

IV. EXPERIMENTATION RESULTS

The base dataset used for this experiment contains 15,893 weather records collected from December 21st, 2011 to January 9th, 2013 via a personal weather collection station at 15 minute intervals. Each tuple contains measurements for the following 14 variables: observation date, indoor humidity, indoor temperature, outdoor humidity, outdoor temperature, absolute pressure, wind, gust, wind direction, relative pressure, dew point, wind chill, wind level, and gust level. But for simplification purpose in this work they consider only following attributes: Minimum temperature, Maximum Temperature , humidity and pressure , were the indoor and outdoor humidity values are converted into single range value , absolute and relative pressure are converted into single pressure. While there are certainly much richer datasets available from meteorological databases, this dataset was intentionally chosen because it is imperfect. The specific reasons for using this dataset in the experiment are explained next.

The following reasons indicates choosing the poor dataset. First, the dataset provides an opportunity to see how neural networks handle datasets with large date gaps. For instance, there is a large gap in collected data from October 12th 2012 to December 29th, 2012. Second, the dataset pertains to a geographic location of interest (Statesboro, Georgia). Finally, the dataset contains many tuples (506 to be exact) with null values. Even high end weather collection systems occasionally fail to collect measurements due to power outages, failed sensors, etc. Since it is useful to assess how neural networks would perform over periods of time in real environments where measurements may occasionally be flawed, this dataset is

considered valuable.

Roll-up Dataset Generation; Before describing the dataset, it is helpful to know the concept of rolling up as it pertains to this experiment. The traditional data warehousing concept of roll-up usually refers to data aggregation from a lower granularity to a higher granularity [19]. In this experiment, temporally rolling up the base dataset will generate the derived attributes which are not available in the base dataset that can be used as neural network inputs. For example, a 24-hour roll-up contains a temperature attribute which indicates the minimum temperature observed over the past 24 hours. This information is not available in any tuple in the base 15-minute interval dataset. Time functions were applied to the base dataset described above to generate 1-hour, 6-hour, and 24-hour datasets containing 3991, 672, and 173 tuples, respectively. In this experiment, quantitative precipitation forecasts and rain/non-rain event classifications were not generated for several reasons. First, the original dataset does not contain enough rain events to allow a neural network to train effectively. Second, rainfall is traditionally a very difficult weather phenomenon to predict, even with rich datasets that span decades [21].

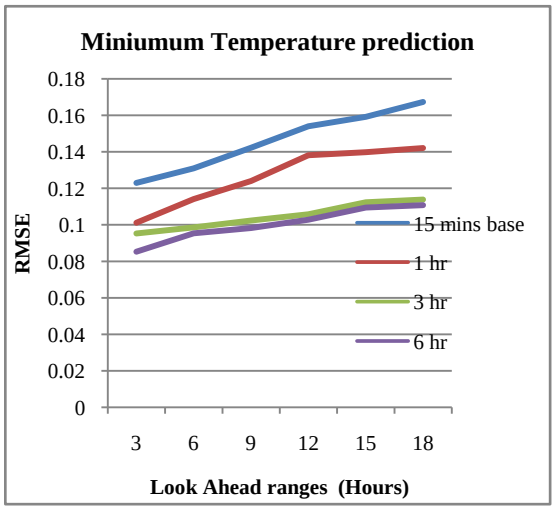

Figure 1: Minimum Temperature Prediction using the Artificial Neural Network (ANN)

Figure1 shows the results for applying ANN on the experimental datasets to conclude minimum temperature predictions more specified look-ahead ranges. Each figure shows the performance of a given Neural Network type across various datasets as measured by Root Mean Square Error (RMSE) values calculated at the 15-minute, 1-hour, 3-hour, 6-hour look-ahead ranges. A RMSE prediction threshold line is drawn at 0.1, although this value was arbitrarily chosen.

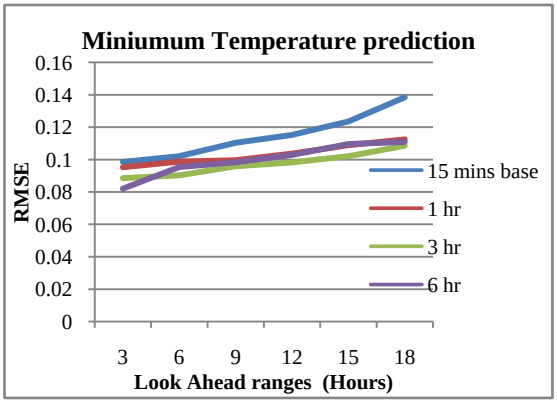

Figure 2: Minimum Temperature Prediction using the Deep Feed Forward Neural Network (DFFNN)

Figure 2 shows the results of applying DFFNN on the experimental datasets to determine minimum temperature predictions over specified look-ahead ranges. Each Figure 2 shows the performance of a given neural network type across various datasets as measured by Root Mean Square Error (RMSE) values calculated at the 15-minute, 1-hour, 3-hour, 6-hour look-ahead ranges. A RMSE prediction threshold line is drawn at 0.1, although this value was arbitrarily chosen

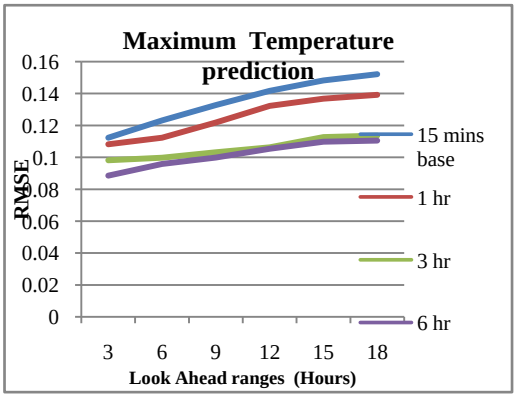

Figure 3: Maximum Temperature Prediction using the Artificial Neural Network (ANN)

Figure 3 are the results of applying ANN on the experimental datasets to determine maximum temperature predictions over specified look-ahead ranges. Each figure shows the performance of a given Neural Network type with different datasets which are measured by Root Mean Square Error (RMSE) values calculated at the 15-minute, 1-hour, 3-hour, 6-hour look-ahead ranges. A RMSE prediction threshold line is drawn at 0.1, although this value was arbitrarily chosen.

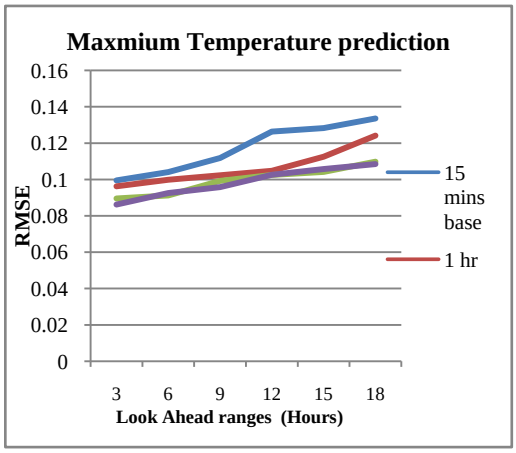

Figure 4: Maximum Temperature Prediction using the Deep Feed Forward Neural Network (DFFNN)

Figure 4 shows the results of applying DFFNN on the experimental datasets to determine maximum temperature predictions over specified look-ahead ranges. Each Figure 4 shows the performance of a given neural network type across various datasets as measured by Root Mean Square Error (RMSE) values calculated at the 15-minute, 1-hour, 3-hour, 6-hour look-ahead ranges. A RMSE prediction threshold line is drawn at 0.1, which is chosen arbitrarly. Good RMSE value will vary from application to application depending on what is acceptable to end users and there is no universally meteorological standard. For this experiment, an average variation of 10% between the squared differences of predicted and observed values is acceptable. Any points that fall above this threshold line represent poor forecasts and any points that fall below this threshold represent feasible forecasts.

F-Measure: F-measure is based on a combinatorial approach which depends on both precision and recall. Each pair can fall into one of four groups: if both objects belong to the same class and same cluster then the pair is a True Positive (TP); if objects belong to the same cluster but different classes the pair is a false positive (FP); if objects belong to the same class but different pair of order is a False Negative (FN); otherwise the objects belong to different classes and different order, and the pair is a True Negative (TN). The Rand index is simply the accuracy;

$$RI = Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (6)$$

The F-measure is another measure commonly used in the IR literature, and is defined as the harmonic mean of precision and recall; i.e.,

$$F - measure = \frac{2PR}{(P + R)} \quad (7)$$

$$Precision(P) = \frac{TP}{(TP + FP)} \quad (8)$$

$$Recall(R) = \frac{TP}{(TP + FN)} \quad (9)$$

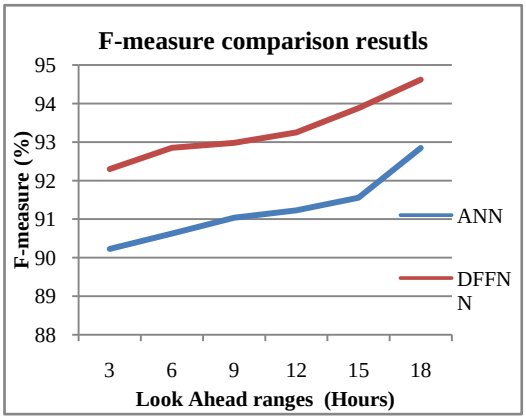

Figure 5: F measure Prediction Results using the Deep Feed Forward Neural Network (DFFNN) and Artificial Neural Network (ANN)

Figure 5 shows the F-Measure results of applying ANN and DFFNN on the experimental datasets to determine maximum temperature predictions over specified look-ahead ranges. TSM with classifier performs well when

compare to ANN, and the F-Measure variation is 1.67 % (94.62 %) high when compared to ANN 92.85 % across Roll-up Dataset. It is reasonable because fuzzy outlier removal is performed to remove missing and incomplete Roll-up Dataset; it is also good F-Measure results at obtaining more Roll-up Dataset by learning from DFFNN the results are tabulated in Table 1.

Table 1: F measure Prediction Results using the Deep Feed Forward Neural Network (DFFNN) and Artificial Neural Network (ANN)

Algorithm name	F-measure (%)	Look Ahead Ranges (Hours)					
		3	6	9	12	15	18
ANN		90.23	90.63	91.04	91.23	91.56	92.85
DFFNN		92.3	92.85	85.12	92.98	93.88	94.62

Table 2: Accuracy Prediction Results using the Deep Feed Forward Neural Network (DFFNN) and Artificial Neural Network (ANN)

Algorithm name	Accuracy (%)	Look Ahead Ranges (Hours)					
		3	6	9	12	15	18
ANN		90.86	91.2	91.56	92.14	92.87	93.21
DFFNN		93.25	93.84	94.53	95.81	93.88	96.85

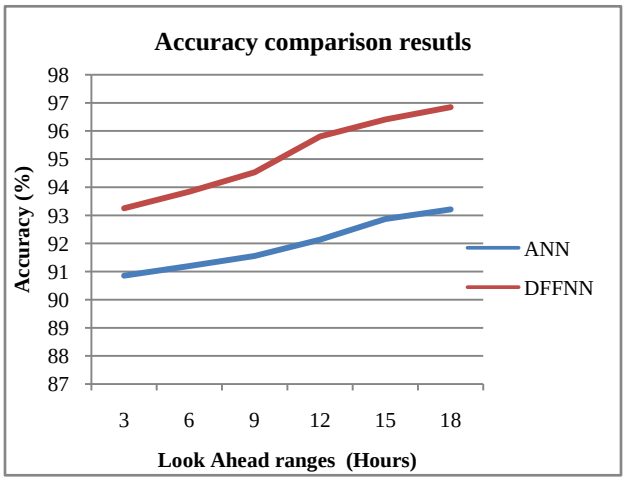

Figure 6: Accuracy Prediction Results using the Deep Feed Forward Neural Network (DFFNN) and Artificial Neural Network (ANN)

Figure 6 shows the accuracy results of applying ANN and DFFNN on the experimental datasets to determine maximum temperature predictions over specified look-ahead ranges. TSM with classifier performs well when compare to ANN, and the accuracy variation is 1.67 % (94.62 %) high when compare to ANN 92.85 % across Roll-up Dataset. It has some reasons because fuzzy outlier removal is performed to remove missing and incomplete Roll-up Dataset; it is also good accuracy results at obtaining more Roll-up Dataset by learning from DFFNN the results are tabulated in Table 2.

V. CONCLUSION AND FUTURE WORK

In our proposed work, the effectiveness is examined using Deep Feed Forward Neural Network (DFFNN) to forecast weather variables, both in existing research and with an experimental dataset. Incomplete dataset samples is removed through data preprocessing which is a common step in many applications, such as data mining, data warehousing, and optimization problems. The data preprocessing plays a very important role in neural networking and then data normalization is examined by using the fuzzy concept. Scaling in data normalization is carried out using fuzzy technique which converts the original dataset samples into fuzzy values which is between 0 and 1. The main goal of this paper is to determine the feasibility of the variables using a rather imperfect dataset which is obtained from a single

collection unit as well as given to neural networks in order to obtain good regression. Deep Forward Neural Network (DFFNN) and Artificial Neural Network (ANN) predictions methods for various weather variables of interest are also used. The weather variables depends on temperature (maximum or minimum), relative humidity, pressure etc., that vary continuously with time and forming time series of each parameter. The variables can be used to develop a forecasting model either statistically or using some other classification methods. 15-minute dataset produces forecasts more accurate than using rolled-up datasets. For rolled-up datasets, loss compensation of available training tuples are not satisfied one compared to the derived attributes in the training tuples. It is clear from this observation that the general idea of neural networking has more examples of training data of neural network processes and the more successful one will be in regressing or classifying variables. There are many possibilities to expand this experiment into future work. The effect of incorporating a distributed computing architecture is examined based on convergence times and forecast accuracy. In order to determine their forecasting capabilities, train neural networks from a more recent dataset and subsequently use them as real-world forecasting system. This is the main reason behind the formulation of an intelligent hybrid systems that overcomes the limitations of neural networks and fuzzy systems. Fuzzy systems are required to have an automatic adaption procedure which is comparable to neural networks. Hybridizing technique has both advantages and disadvantages.

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