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WEATHER PREDICTION BY INTEGRATING RECURRENT NEURAL NETWORK DYNAMICS INTO CASE BASED REASONING

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Abstract *Most of the weather forecasting approaches attempt to forecast only single weather attribute at a time (e.g., temperature, rainfall etc.). If weather attribute(s) is forecasted by Case Based Reasoning (CBR) then similarity between cases is measured by a similarity metric where equal weights or heuristic weights are assigned to all influencing attributes. This paper presents a forecasting method for one day-ahead prediction of multiple weather attributes at a time by case based reasoning (CBR) in local scale, which resolves the attribute weighting problem of CBR using non-linear autoregressive with exogenous inputs neural network (NARXNN) and results a hybrid method for multiple weather attributes forecasting.*

Forecasting performance of simple CBR, segmented CBR and hybrid CBR by NARXNN is compared. From the experimental results, superiority of the hybrid method to others is established in forecasting of multiple weather attributes. Collected historical records of weather station from 1980 to 2009 are used for model training, validating and testing

Keywords: *Case Based Reasoning, Artificial Neural Networks, NARXNN, Integrated System, Machine learning, Weather Forecasting*

Introduction

Weather is one of the most important environmental constraints in every step of our lives. We are often ready to adjust ourselves according to weather conditions, from our dressing habits to planning activities since weather conditions may have a considerable effect on our lives and property. Weather forecasting acts as a warning to us and is also important for agriculture and traders within commodity market. Thus it is required to have an alert to weather conditions for taking some precautions. Weather forecasting is an application of science and technology to predict the state of the atmosphere for a location at a particular instance of time. It is the prediction of what the weather will be like in an hour, a day or a week and so on.

There are usually two methods to predict weather: (i) the empirical approach and (ii) the dynamical approach (Lorenz, 1969). Riordan and Hansen (2002) have explained this classification as the empirical approach that is based upon the happenings of comparable cases (i.e., similar weather situations) and is powerful and useful for predicting local-scale weather if recorded cases are plentiful. The dynamical approach that is based one quations of the atmosphere, is commonly referred to as computer modeling and only useful for modeling large-scale weather phenomena (e.g., general wind direction over a few thousand square kilometers).

With the advent of technology, Internet, and efficient communication, meteorological department collects a huge amount of relevant and invaluable data which are not properly mined and not organised for optimum use. Discovery of these hidden patterns and their relationships often goes unexploited and unknown. Due to this reason weather predictions are often made based on meteorologist's intuition, experiences, and defined time function rather than on the knowledge of data hidden in the database. Sometimes, this approach may lead to unnecessary errors in meteorological prediction. Therefore, this paper includes artificial intelligence components in local weather prediction using empirical approach to capture weather dynamics for better weather forecasting by eliciting the knowledge of data hidden in the database for prediction.

Various intelligent techniques have been extensively used in weather forecasting but quite a number of difficulties have affected these systems. CBR is recommended to developers to avoid repeating mistakes made in the past, reason in domains that have not been fully understood or modelled, learn over time, reason with incomplete or imprecise data and concepts, provide a means of explanation, and reflect human reasoning. Therefore CBR is now being adopted in prediction and forecasting. Riordan and Hansen (2002) have developed a fuzzy case based system for weather prediction where fuzzy logic is used to capture climatological behaviour and heuristic weights are used in case observation. Li and Liu (2002) proposed a fuzzy case based reasoning approach to forecast a single attribute (only visibility) by capturing continuous, dynamic and chaotic process of weather using timing function and power weights. Singh, Ganju,and Singh (2004) and Singh and Ganju (2006) have presented a CBR model to predict weather in terms of snow/no snow day and the amount of snowfall (snow height in cm) for three consecutive days in advance using case based reasoning approach. Lu, Wang, and Zheng (2012) presented a CBR based weather forecast system which predicts multiple weather elements at the same time. Ibrahim (2012) developed a model by case based reasoning for weather forecast text generation where the wind data is the problem and the forecast text is solution. Zubair, Khan,and Awais (2012) have proposed a CBR approach to predict and analyse the air accidents and incidents with satisfactory accuracy. Liand Xiong (2012) have developed a model by case based reasoning to predict business risk. Guang-qun, Bao-ping, and Hang-jun (2010) developed a CBR model for bamboo snout moth forecasting. Rong, Rongqiu Xia, and Guoping (2008) have proposed a case based reasoning system for individual demand forecasting. Wang (2006) has developed a CBR system to solve short term load forecasting problem with the aid of self-organizing maps (SOM) and fuzzy rough sets method. Kise, Mitsuishi, and Kosuge (2003) proposed a case based reasoning approach for prediction support system of lightning flash. Alberola and Garcia-Fornes (2013) have proposed a case-based reasoning model for trading in sports betting markets. Rishi and Chaplot (2010) presented a model for astrological predictions about profession using case based reasoning.

In earlier CBR weather forecast systems, k-NN method or its variants were widely used as the retrieval mechanism (Riordan & Hansen, 2002). However, the most important assumption of k-NN is that all of the attributes presented are equally important and thus assigned equal weights. This handicaps the k-NN by allowing the irrelevant features to influence the forecasting and thus the system performs poorly. This paper determines the attributes' weight by artificial neural network (ANN) for case based reasoning (CBR). A number of weather forecast systems using AI components and data mining tools have also been developed but most of them are for a single or particular weather attribute rather than multiple weather attributes predictions at one time and the dynamic behaviour of the weather phenomena is not taken into account scientifically and logically as dynamics of weather is captured by using heuristic time function equations. They also have some other severe problems. For example, the justification and aptness of CBR in weather forecasting is established in Riordan and Hansen (2002) but it lacks in attribute weight assignment to measure similarity between cases. Even if weights for different observations (case points) of a case are assigned but it is expert defined, not knowledge mined from past historical data. Liand Liu (2002) have forecasted a single attribute (only visibility) by capturing continuous, dynamic and chaotic process of weather using timing function and power weights. The model in Singh, Ganju, and Singh (2005) lacks in attribute weight assignment to measure similarity between cases. Kiskac and Yardimci (2004) have proposed a weather forecasting methodology by taking probability distribution of the similar cases but it also lacks in attribute weight assignment to measure similarity between cases. The method in the research paper by Lu, Wang, and Zheng (2012) is heavily dependent on the human forecast experiences and time function equation.

But, weather dynamics can't be captured properly by using heuristic time function equations as different locations have different climatological behaviours, so it is better and justified to capture the weather dynamics by generalising local climatological information of a location for local scale weather forecasting as weather dynamics and local effects encountered in meteorological data. ANNs are endowed with some unique properties, like the ability to learn from and adapt to their environment and the ability to approximate very complicated mappings using available information. Many previous works have used ANN for weather forecasting (Routh, Bin-Yousuf, Housain, Asasduzzaman, Hossain, Husnaeen, & Mubark, 2012; Jin, Lin, & Lin, 2006; Kumar, Kumar, Ranjan, & Kumar, 2012; Nayak, Patheja, & Waoo, 2012). Nayak, Patheja, and Waoo (2011) have proposed a model for prediction of temperature, wind speed, and relative humidity by using a trained ANN. Erdiland Arcaklioglu (2013) have also proposed a model for predicting atmospheric pressure and solar radiation by using ANN model. But in those researches the forecasting is done only for one/two/three element/elements at a time such as temperature, precipitation, or rainfall. Non-dynamic ANNs have been used to find the input/output relationship of the meteorological data. Thus, they have neglected the dynamic and continuous characteristics of the weather data.

In order to make a practical weather forecasting model, it must need to take care about some important issues that are inherent in weather forecasting. Extracting appropriate knowledge from meteorological data and consideration of weather dynamics and local effects are important. Sometimes it may also happen that the weather of a particular season diverts for a few days and it may abstract the weather feature values differently and there is also possibility of abrupt changes for a day or two. Thereforea case should be represented in such a way that can capture and treat all those changes nicely.

Non-linear autoregressive with exogenous inputs neural network (NARXNN) is a dynamic neural network that can capture the dynamic behaviour of dataset being encountered and can be used in time series prediction to predict the next value of the series using the historical data because NARXNN has already been used in time series prediction due to its capabilities in (Menezes & Barreto, 2006; Diaconescu, 2008; Xie, Tang & Liao, 2009; Arbain & Wibowo, 2012; Menezes Jr & Barreto, 2006).

In view of that, this paper presents an integration of CBR with NARXNN to design a weather forecasting system that predicts multiple weather attributes at the same time. The objective of this work is to forecast one-day-ahead i.e. D_{n+1} weather attributes by considering weather attributes of the previous n days i.e.D_1, D_2, D_3, ...,D_n.

The paper is organised as follows: An introduction of CBR, NARXNN and integration of CBR with ANN is described in second, third, and fourth sections respectively. The research methodology of the proposed model is described in fifth section. Experiments and results are reported in sixth section. Lastly conclusion of the approach is drawn in seventh section.

Case Based Reasoning

Case-Based Reasoning (CBR) is an artificial intelligence approach to learning and problem solving based on past experiences stored in a case base. It also captures new knowledge/experiences, making it immediately available for solving next problems. These experiences encode relevant features/attributes, courses of action that were taken, and solutions that ensued. The case-based reasoner works by using a similarity measure to retrieve past problems that are most similar to the current problem. The reasoner then adapts the solutions of the most similar past problems to generate a proposed best solution to the current problem. Thus, the design of similarity measure and adaptation algorithm is crucial to the functionality of any case-based reasoner. In abstract view of CBR method at least four tasks i.e. retrieve, reuse, revise, and retain, are required to complete the CBR cycle.

Retrieval is an important step in the CBR cycle, which retrieves the previous case(s) that can be used to solve the target problem. The retrieval phase starts with a partial problem's description, and ends when finds the most similar previous case(s). A similarity measure is usually defined by a formula to calculate the similarity between previous cases and the new case. In this paper, each retrieved case represents a previously encountered climatological situation that is similar to the current situation. Reuse is a task just after case retrieval and is responsible for proposing solution to new problems from retrieved cases. There are two ways of previous case reuse: solution reuse and method reuse. In the solution reuse, the past solution is not directly copied to the new solution if the new case is not exactly same as past case(s) but there is some knowledge allowing the previous solutions to be fit into the new case solution. In method reuse, it is observed how the problem was solved in the retrieved cases. The objective of revise phase is to evaluate the retrieved solution. If the retrieved solution is fit for new case, it is possible to learn about the success, otherwise the solution is repaired/adapted using some problem domain's specific knowledge or any other ways. Retain phase consists in a process of integrating the useful information about the new case's resolution in the case-base.

Non-Linear Autoregressive with Exogenous Inputs (NARX) NN

Non-linear autoregressive with exogenous input model is a type of recurrent neural network defined by the following equation (1):

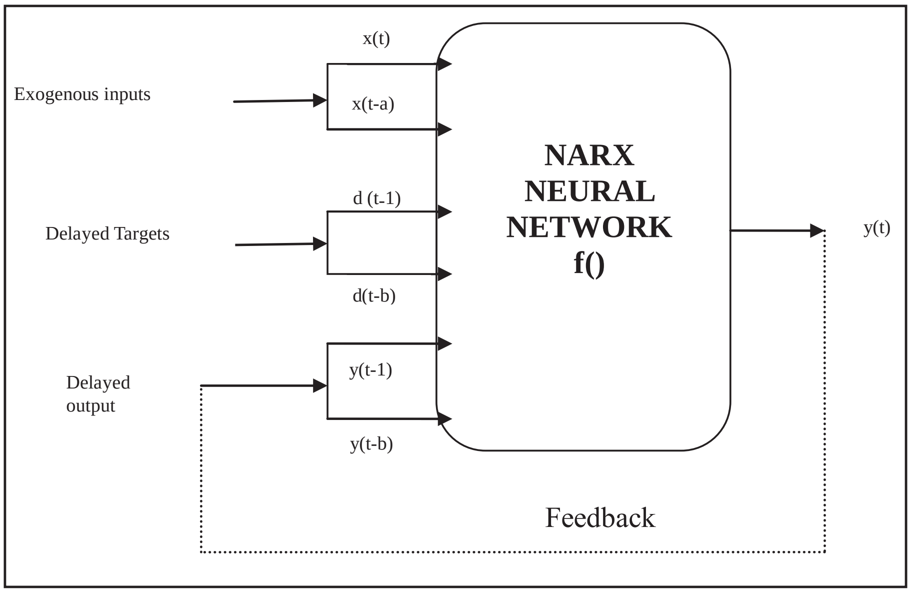
$$Y(t) = f(x(t),...,x(t-a),y(t-1),...y(t-b),d(t-1),....d(t-b)) \quad (1)$$

Where d represents the targets for the time series that is to be predicted, $y$are the past predicted values (actual output of the network) of the model, a and b are the input and the output order, x is the exogenous variable and f is the nonlinear function. The purpose of the NARX model is to predict the next value of the time series taking into account other time series that influence the next value to be predicted and also past values of the series or past predictions. In this model, variables that influence the value of the time series, the one to be predicted are exogenous variables. The input order gives the number of past exogenous variables that are fed into the system. In general, the exogenous variables are time series. The exogenous variables' values can be used starting from current time t until $t – a$, where a is the input order. The input variables along with their order are called the input regressor.

y represents the past predicted values. Because it is required to predict the value at the current time t, values starting from $t – 1$ to $t – b$ can be used, where b is the output order – the number of past predictions fed into the model. These past predicted values along with their order are called the output regressor. The targets *d* represent the desire values of the time series that are required to predict, which are also fed into the system. The same order as for past predicted values is used

With the above notations, the output of the network for the time *t*, the prediction, is *y(t)*. The NARX model is trained using dynamic BP neural network. The architecture of the NARX model is shown in Fig. 1.

Fig. 1: NARX NN



Integration of CBR and ANN

Even though CBR methodology has been successfully applied in many applications, CBR suffers from the feature-weighting problem as when CBR measures the distance (similarity) between cases, some input features should be treated as more important than other features. If feature weighting is executed prior to prediction in order to provide the information on the feature importance, then prediction accuracy would be good enough. Hence, even though there are many successful applications based on standard CBR methodology, its performance can be significantly improved when combined or augmented by other machine learning or data mining technologies, which can find feature importance. A possible integration is CBR-ANN in which the feature weights are set by the trained neural network, as it plays the core role in connecting both learning strategies, and retrieving the most similar cases from the case base. To exploit the meritorious features of both CBR and ANN, they may be integrated for designing improved and more intelligent systems (Jani & Islam, 2012). Motivated by the impressive performance of ANNs many researchers have implemented CBR systems coupled with ANNs (Shin, Yun, Kim, & Park, 2000; Yuan, Mao, & Zhao, 2010; Chuang, 2011). Furthermore Zhang and Yang (2001) have used weights obtained from a neural network for ranking scores of the cases in a case base for efficient case retrieval, Park and Im (2004) have proposed an integrated learning framework of neural network and case-based reasoning (Memory Based Neural Reasoning) in which feature weights for case-based reasoning can be evaluated by neural networks. Ha(2008) proposed CANSY algorithm which adopts a trained neural network for feature weighting and a value difference metric in order to measure distances between all possible values of symbolic features that plays a core role in classifying and presenting most similar cases from a case base.,An integrated learning framework of neural network and case based reasoning has been proposed by Park, Shin, Im, and Park (2001) who demonstrated its performance of the learning system using the sinusoidal dataset. Ni, Lu, Li, and Jia (2002) designed an efficient case-based system with neural network, which is applied to flood disaster prediction problem in weather prediction field. Dong (2010) proposed an electronic negotiation model based on neural network and case-based reasoning. Peng and Zhuang (2007) applied a hybrid case-based reasoning method that integrates a multi-layer BP neural network with case-based reasoning for derivatives feature weights, which is applied to fault detection and diagnosis system. Thus, the performance of the CBR systems can be successfully improved when combined with ANNs.

Research Methodology

To forecast multiple weather attributes at a time, case is properly represented and case base is organised by all possible cases without repetition of a case. The case base is segmented to capture the behaviour of seasonality as pre-processing of the proposed model. In order to forecast, CBR approaches and integration of CBR and NARXNN model are applied. In this section, a detailed explanation about each stage is provided.

Pre- Processing

Case Representation

The experience of a case can be represented in various ways. Very often it is subdivided into a problem and solution descriptions. Weather is a continuous description of the cyclic changing state of the atmosphere. The characteristics of the weather elements are known to be repeating over a period of time for a region, so there will be a situation in past which is very similar to the present condition (target case). It implies that the present weather condition on certain consecutive days will be similar to the weather condition of some previous consecutive days. Therefore, it is required to find out the number of case points that can capture the cyclic similarity of the weather of Austin. By using standard CBR method, the number of case points, m is varied from m=3 to 15 days as shown in Table 1 and the accuracy of the standard CBR is measured by cross validation. From Table 1, it is observed that when m=7, it obtains highest accuracy. This shows that with seven case points in one case it can capture the cyclic similarity of Austin's weather better.

Table 1: Performance by Different Number of Case Points

Number of Case Points	Accuracy (%)
3	66.18
4	68.48
5	65.37
6	67.38
7	**72.45**
8	63.16
9	68.10
10	64.83
11	67.30
12	68.70
13	67.65
14	66.62
15	68.60

Table 2: Representation of a Case

Day	Date	Month	Year	Mean Temp	Mean Dewpoint	Sea Level pressure	Station Pressure	Visibility	Wind Speed	Max Speed	Max Temp	Min Temp
day1	--	--	--	84.4	70.8	1014.4	992.9	11.9	3.7	8	96.1	73
day2	--	--	--	83.2	70.8	1015.2	993.7	13.6	4.1	11.1	95	73
day3	--	--	--	83.7	70.3	1013.9	992.6	14.9	6.2	13	93.9	77
day4	--	--	--	80.7	71.2	1011.6	990.1	13.6	5.9	11.1	93.9	73.9
day5	--	--	--	82.9	71.1	1011.1	989.8	14.9	9.8	20	93.9	75
day6	--	--	--	82.3	71	1013.4	992	13.8	7.6	13	95	75
day7	--	--	--	84.2	69.6	1013.3	991	14.9	8.6	14	95	73

Thus in order to forecast weather, a case is defined as a set of 7 consecutive days (7 case points). The first 6 days (6 case points) represent the problem description of the case and the 7^{th} day represents the solution description of that particular case.

Let $a(t)=\{a_1(t), a_2(t),\ldots\ldots\ldots\ldots\ldots a_m(t)\}$ represent a set of m attributes observed in one day. Each row (each case point) contains one day observation made in day t and each observation consists of m=12 attributes (weather attributes are grouped into 9 columns and it also includes temporal attributes such as date, month and year of the day in first 3 columns). Table 2 shows the representation of a case (one data point) in case base.

In order to predict the next day's weather attribute values the first six rows (six case points)are presented as an input, i.e. from day 1 to day 6 and attribute values of day 7 (last case point of the case) are predicted by the system as output.

Case Base Organisation

The organisation of cases (data) in a case base (database) is an essential part of a CBR system. One case point consists of a set of weather attribute values of a day and a set of seven case points constitutes one case. Initially the subsets of cases are formed by considering that a case base contains n rows and R_i represents a row into the database where $1\leq i\leq n$. The first subset (S_1) of cases consists of $\{(R_1, R_2, \ldots, R_7),(R_8, R_9, \ldots,R_{14}), \ldots., (R_{n-6}, R_{n-5}, \ldots R_n)\}$ type of patterns. Similarly other subsets are formed so that the subsets are $S_1 = \{(R_1, R_2, \ldots, R_7), (R_8, R_9, \ldots, R_{14}), \ldots, (R_{n-6}, R_{n-5}, \ldots R_n)\}$, $S_2 = \{(R_2, R_3, \ldots, R_8), (R_9, R_{10}, \ldots, R_{15}), \ldots, (R_{n-12}, R_{n-11}, \ldots R_{n-6})\}$, $S_3 = \{(R_3, R_4, \ldots, R_9), (R_{10}, R_{11}, \ldots, R_{16}), \ldots, (R_{n-11}, R_{n-10}, \ldots R_{n-5})\}$, $S_4 = \{(R_4, R_5, \ldots, R_{10}), (R_{11}, R_{12}, \ldots, R_{17}), \ldots, (R_{n-10}, R_{n-9}, \ldots R_{n-4})\}$, $S_5 = \{(R_5, R_6, \ldots, R_{11}), (R_{12}, R_{13}, \ldots, R_{18}), \ldots, (R_{n-9}, R_{n-8}, \ldots R_{n-3})\}$, $S_6 = \{(R_6, R_7, \ldots, R_{12}), (R_{13}, R_{14}, \ldots, R_{19}), \ldots, (R_{n-8}, R_{n-7}, \ldots R_{n-2})\}$ and $S_7 = \{(R_7, R_8, \ldots, R_{13}), (R_{14}, R_{15}, \ldots, R_{20}), \ldots, (R_{n-7}, R_{n-6}, \ldots R_{n-1})\}$. The final case base is organised by taking the union of all these subsets of cases and thus the case base is formed by the all possible cases without repetition of a case.

Case Base Segmentation

A year of Austin consists of four seasons and each season has a particular range of weather attribute values and some characteristics. For instance,the temperature of summer is higher than that of winter or there is less rainfall. There are also different correlations among the weather attribute values for different seasons. The existence of four seasons is repeated at the same time every year. But it is also natural that sometimes the weather of a particular season diverts for a few days and abstracts the weather attribute values of a different season. For instance, there is heavy rainfall in winter days. If the case-base is not segmented, exceptional cases will also be included in the set of similar cases during retrieval mechanism and thus it lowers down the accuracy of the forecasting system. In order to avoid these exceptions the database is partitioned into four segments depending on the behaviour of the climate. This also reduces the time complexity of the search. As the weather data of Austin is used,the division is made based on the climatic condition of Austin. Three attributes are considered for the region; these are mean temperature, precipitation, and pressure. According to their behaviour, the whole database is divided into four segments (winter, spring, summer and autumn). The graphs of the behaviour of mean temperature and precipitation are shown in Fig. 2 and Fig. 3 respectively. Table 3 shows how a year is divided into four seasons.

Fig. 2: Mean Temperature of Austin City, Texas

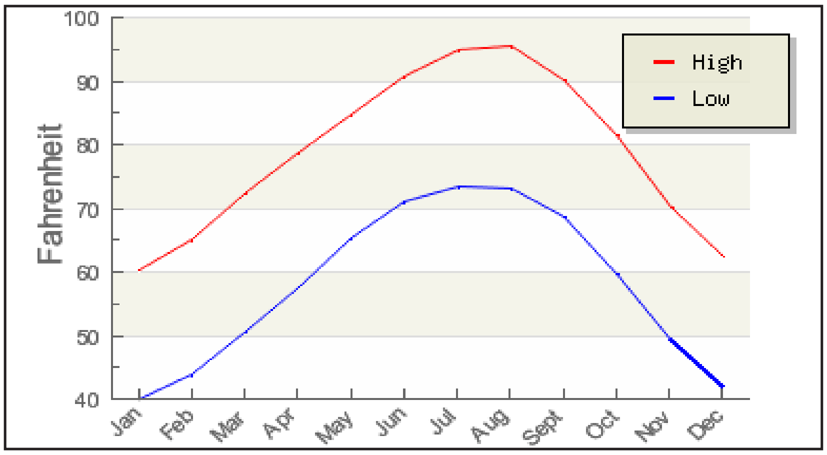


Fig. 3: Average Precipitation of Austin City, Texas

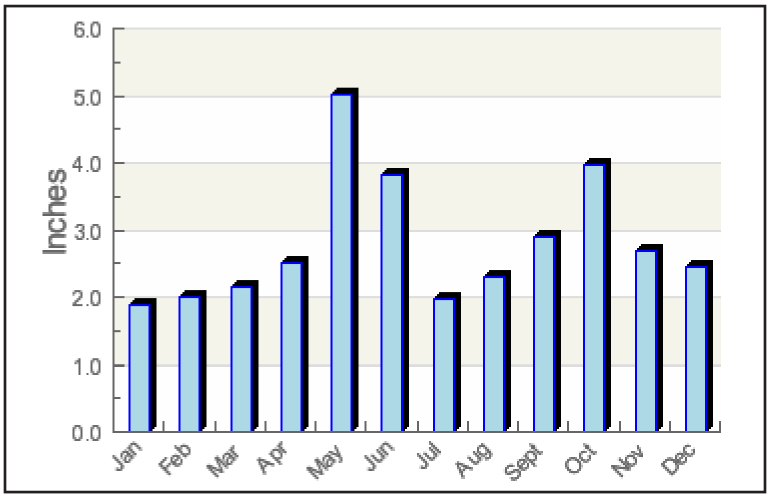


Table 3: Segments of Database

Segment	Months
Segment 1 (Winter)	December, January, February
Segment 2 (Spring)	March, April, May, June
Segment 3 (Summer)	July, August, September
Segment 4 (Autumn)	October, November

When a new case is presented for forecasting, it is indexed to the relevant segment. This is done by considering the month of the new case and accordingly the segment is determined. In case of an overlap, only the segment containing the majority of rows is considered. But if there is an equality of rows both the segments are considered as a segment for that new case. Once the segment is determined searching and retrieving of similar cases from that particular segment arestarted.

Methods

Prediction methods using simple CBR, segmented CBR and integration of CBR and NARX NN are implemented. The detailed explanation of the integrated method is given below.

CBR and NARXNN Integrated Forecasting Method

In the proposed hybrid system, NARXNN acts as a co-reasoner, which works in parallel with CBR and assists the reasoning paradigm of CBR. NARXNN is used to learn the relationship among the data in the database, i.e. training set and is capable of identifying the cases most similar to a new case as the trained neural network stores its knowledge in the connection weights among the neurons and finds the similarity between the new case and the cases stored in the case base.

Network dissimilarity measure is used to retrieve the top most similar cases of the new case from the case base. The network dissimilarity measure uses a trained neural network to estimate similarity between two cases. To find the similarity between the new case and the cases stored in the case base, each input in the input set is the difference between corresponding feature values of the new case and a case stored in the case base. The input set comprising such inputs is fed to the network and from the network output set; the estimation of the distances between the new case and the cases stored in the case base is made. The case stored in the case base for which the output of the network is minimum, is considered as the closest case to the new case.

The basic building block for ANN is an artificial neuron or a node. Nodes in the neural network are organised into layers. Every node in one layer has weighted connections to every node in the next layer. A node receives inputs $x_1, x_2, ..., x_n$ through its n input connections. If the associated weights to those connections are $w_1, w_2, ..., w_n$ then the sum of weighted inputs (Net) for the node is given by equation (2).

$$Net_i = \sum_j w_{ij} x_j \qquad (2)$$

To determine whether the sum is large enough to excite the node, an activation function is applied on the weighted sum of inputs to generate an output value that represents the excitement or activation level of the node. The most common form is the sigmoid function, defined by equation (3).

$$f(Net) = \frac{1}{1+e^{-Net}} \qquad (3)$$

Since each input in the input set fed to the network is the difference between corresponding attribute values of the new case and a case stored in the case base, the Net will be a smaller value comparatively if a case stored in the case base is the most similar to the new case. Therefore, e^{-Net} will be larger, and hence f(Net) will be smaller. That is why the case in the case base for which the output of the network is minimum, is considered as the closest case to the new case. This is the main working principle of the proposed integration system.

The framework of the hybrid CBR model is shown in Fig.4. For each segment one NARXNN is trained to capture knowledge about weather data of that segment in network links. When a target case is encountered in case retrieval module, it is indexed to the corresponding segment and the trained NARXNN of the corresponding segment is used to find k most similar cases. Then case reuse and revision module is used to propose a solution which is sent to the target case where it is required. After pre-processing, the hybrid CBR for forecasting follows the steps which are given below:

Stage-1: Case Selection

Retrieval of most similar cases is very critical to the success of a CBR system. In this model, the method implemented for determining similarity in CBR, employs a trained NARXNN. The primary advantage of using this method is that it accurately estimates complicated similarity functions as compared to the method that incorporates weighted Euclidean metric to retrieve nearest neighbour cases. Hence, NARXNN is integrated into CBR to form a hybrid system.

In this model, the top most similar cases are selected, which are presented in the system to measure the performance of the model. Selection of cases is done by performing the following steps for assessing similarity of past cases to the new case:

- RETRIEVE multi-attribute based information of past cases by NARXNN.
- MATCH past cases with the new case using network dissimilarity based search.
- COMPARE past cases with each other by the dissimilarity score.

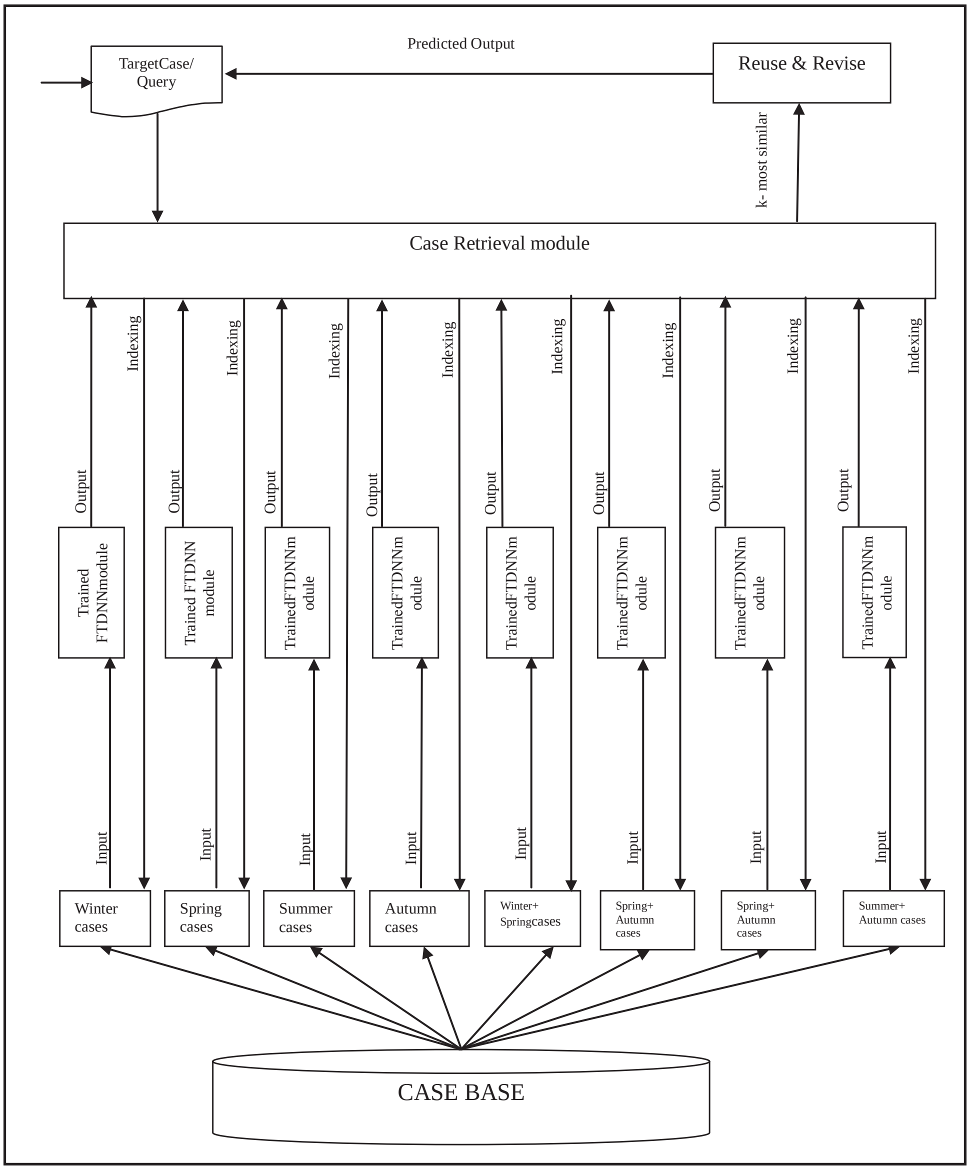
- SELECT past cases having least values of dissimilarity score.

A training set is used to train the NARXNN. An input set is fed to the trained network where each input in the input set is the differences between the corresponding attribute values of a test case and each of the cases stored in the case base. From the network output set, the dissimilarities between the test case and the cases stored in the case base are obtained. The case in the case base for which the output of the network is minimum, is considered as the closest or most similar case to the test case. Thus using trained NARXNN, the top most cases similar to a test case are retrieved from the case base.

Stage-2: Case Reuse and Revision

The top most similar case should be used as the proposed solution for the new case (test case) but unfortunately the most similar case may be an outlier causing performance degradation of the system. To overcome such a situation, a few similar cases are taken into consideration to produce the predicted result by observing weighted sum of solutions of the similar cases. In this model the solution of the most similar case is initially reused as the proposed solution and performance of the system is measured. Afterwards this measured performance is compared with the performance of the model when number of most similar cases, i.e. k, is changed (k=2, 3, ……). It is observed from Fig. 16 that the performance of the system drops down when k increases. The system produces optimal result when k equals to 1. Hence, when a new case comes in, prediction is made to the new case by the top most similar case only.

Fig. 4: The Layout of the Hybrid CBR Forecasting Model by FTDNN



Proposed Hybrid CBR-ANN Weather Forecasting Algorithm

Based on the solutions of the most similar cases, a case-based forecaster performs prediction of a new case. It is necessary to find an appropriate method to measure the similarity between the cases. So a trained dynamic neural network i.e. NARX is used to measure the similarity, which captures quality case attributes and the dynamics of the weather. Suppose each case's problem description consists of m x n elements where m is the number of case points and n is the number of weather attributes in each case point.

Let, $X=\{(x_{11}, x_{12}, \ldots, x_{1n}), (x_{21}, x_{22}, \ldots, x_{2n}), \ldots (x_{m1}, x_{m2}, \ldots, x_{mn})\}$bean input case, and $Y=\{(y_{11}, y_{12}, \ldots, y_{1n}), (y_{21}, y_{22}, \ldots, y_{2n}), \ldots (y_{m1}, y_{m2}, \ldots, y_{mn}), (y_{m+1,1}, y_{m+1,2}, \ldots, y_{m+1,n})\}$bea case stored in the case-base, where $y_{((m+1), n)}$ is the solution description of the case.

The network based similarity measure finds similarity between problem descriptions of cases. The hybrid case based forecaster is blindly not biased on the decision of top most similar case, and hence includes generality and extendibility in forecasting algorithm. The proposed hybrid multiple weather attributes forecasting algorithm is given as follows:

Proposed Hybrid Multiple Weather Attributes Forecasting Algorithm

I_X: problem description of a case, (m x n)
I_Y: solution description of the case, ((m+1)th row with n elements)
O(s): set of actual outputs of the network (1 x n)
D: desired attributes values (1 x n)
Input: set of attributes (m x n)
Output: desired attribute values (1 x n)
Procedure
Step$_1$: case is represented by problem description (I_x) and solution description (I_Y)
//TRAINING PHASE //
Step$_2$: Present cases, each of which is represented by problem description (I_x) and solution description (I_Y)
Step$_3$:[Initialize the network by the architecture until performance of the network is not improved]

a. Determine the architecture: how many hidden neurons and layers
b. Initialize all weights to small random values.
c. Along with the initialisation of the architecture, the training function of the network is initialised.
d. [Repeat until termination criterion is satisfied: (maximum number of epoch or error goal)]
   [i]Present training set of cases and propagate it through NARX network.
   [ii] Present test set of cases and propagate it through NARX network.

// VALIDATING PHASE //

Step$_4$: [Finding most similar cases of test case using network similarity measure] For each case of the test set, do the following:

a. Find the differences between corresponding feature values of the test case and each of the cases of the training set of cases. The resulting set becomes the input set to the network for the test case. An input of the input set is given as,

$$(|X_{mn}-Y(i)_{mn}|)$$

where X_{mn} is an attribute value of the test case and $Y(i)_{mn}$is an attribute value of ithcase in the case-base, m is the number of case points in case's problem description and n is the number of weather attributes in each case point and $1 \le i \le j$ where j is the number of cases in the case base.
b. Present the input set to the trained NARXnetwork.
c. Simulate the network for the input set to obtain O(s)
d. Retrieve the k number of cases of the training set (case base) for which the corresponding outputs of the network are minimum (i.e., minimum dissimilarity score).

Step$_5$: Find weight of different similar cases i.e., 1 to k for forecasting by cross validation.
***Step$_6$*:** Find forecasting outcome and accuracy by weighted sum of k.
Step$_7$:Find the value of k for which highest accuracy of the system is achieved, i.e. optimal k.
Step$_8$: Forecast a new case by weighted sum of optimal k.

Step 1 depicts the structure of a case which consists of a problem description and a solution description of a case. Step 2 depicts that the training cases are made available to be fed to a neural network. In Step 3, a NARX neural network is created,the training set is used to train the NARX network and the best architecture of the neural network is set by test data. Step 4 depicts that the network is simulated with an input set where each input is the differences between corresponding attribute values of a test case from validation set and one of the cases in the training set i.e., case base. At the same time it finds k most similar cases to the test case. Step 5 finds the weights of k most similar cases in forecasting by cross validation. Step 6 and Step 7 find the value of k for which the system produces highest accuracy. Step 8 depicts that when a new case needs to be forecasted, it is forecasted by weighted sum of optimal k.

Experiments and Results

Dataset

The experiments are conducted by using real weather data of 30 years (1980-2009) recorded at Austin. The data is collected on a daily basis and this dataset describes weather with nine weather attributes. Weather data from the year 1980 to 2007 is used as the training set as well as validating set and data of the year 2008 and 2009 is used as test data. The experimentation of the proposed model is done by MATLAB 7.12.0.635 (R2011a) in windows environment.

Performance Measurement

In order to judge how good and reliable the model is, there has to be a method to measure its performance and accuracy. There have been numerous methods to measure the accuracy of the system but the most common measure is the Mean Absolute Percent Error (MAPE). Therefore in this paper, the MAPE has been adopted and it is given for each attribute by equation (4):

$$MAPE_t(\%) = \frac{|A_t - F_t|}{A_t} \times 100 \tag{4}$$

where, A_t is true value of the t^{th} weather attribute, F_t is predicted value of the t^{th} weather attribute.

Thus the accuracy of each weather attribute is given by equation (5):

$$Acc_t(\%) = 100 - MAPE_t(\%) \tag{5}$$

The accuracy of acase is given by equation (6):

$$Accuracy(\%) = \frac{1}{n}\sum_{t=1}^{n} Acc_t(\%) \tag{6}$$

where, n=9 is the total number of weather attributes.

Three weather forecasting experiments are conducted. In the first experiment the casebase i.e., database is not segmented and CBR method is used for weather forecasting using Euclidean distance as the similarity measure. The forecast accuracy is tested by varying k nearest neighbours. It is observed that there is no significant improvement in accuracy after k equals to 20. Hence prediction is made by weighted sum of 20 most similar cases. In the second experiment, the case base is segmented into eight segments (Winter, Spring, Summer, Autumn, Winter+Spring, Spring+Summer, Summer+Autumn, Autumn+Winter) and CBR method is used for weather forecasting using Euclidean distance as similarity measure. Similarly in this experiment the forecast accuracy is tested by varying k nearest neighbours. It is also observed that there is no significant improvement in accuracy after k equals to 20. Hence prediction is made by weighted sum of 20 most similar cases. In the third experiment the proposed integration of CBR and NARXNN (Hybrid CBR) is applied for weather forecasting and it produces optimal result when k equals to 1.The third experiment is briefly described below.

Hybrid CBR Forecasting Model

For each segment, there is a corresponding trained NARXNN which is integrated into CBR to forecast a new case when it belongs to the corresponding segment. There are eight trained NARXNN architectures for eight possible segments (Winter, Spring, Summer, Autumn, Winter+Spring, Spring+Summer, Summer+Autumn, Autumn+Winter). The optimal network architecture is initially found for each segment and then the optimal architecture is integrated into CBR for the corresponding segment. To find the optimal architecture for each segment the number of hidden nodes in the hidden layers is varied between (k+1) to (2k) to determine the number of hidden nodes where k is the number of input nodes. For each architecture, initially all the training patterns of the corresponding segment are presented to the network for training. Then the test cases which fall in the corresponding segment in the test data are simulated by trained neural network to calculate the performance of the network architecture. The network architecture, which gives the highest performance, is taken for further experimentation. Number of layer increases if performance increases by increasing number of layers, otherwise it is stopped. Different architectures of each segment with accuracy are given in Table 4. The optimal architectures of NARXNN for different segments determined by experiments are given in Table 5. The regression plots of optimal architectures of training phase are shown in Fig. 5-12. The regression plots are made with the normalised values (-1 to +1) of the attributes as well as actual values of the attributes for better understanding. It is observed from regression plots that the relationship between problem and solution parts of cases is not straightforward because they do not show linear trend in the data (problem and solution parts of cases cases).

The trained NARXNN is integrated into CBR and thus each possible segment has a corresponding hybrid CBR model to forecast a new case when it belongs to the corresponding possible segment.

Training is done by input-output mapping of the corresponding segments with tapped delay lines equal to 2, where input means problem description of a case and output means solution description of the case. The standard Lavenberg-Marquardt back propagation algorithm is used to train the network with learning rate equals to 0.01. The method regularisation is used which consists of 1000 epoch and regularisation parameter used is 1.00e-05. Training automatically stops when generalisation stops improving, as indicated by an increase in the Mean Square Error (MSE) of the validation samples.

Table 4: Architectures of Each Eegment

Winter			Spring			Summer		
Architecture	**Training Accuracy%**	**Testing Accuracy%**	**Architecture**	**Training Accuracy%**	**Testing Accuracy%**	**Architecture**	**Training Accuracy%**	**Testing Accuracy%**
6-7-1	97.34	91.27	6-7-1	99.2	83.61	6-7-1	95.9	92.14
6-8-1	95.1	92.89	6-8-1	96.4	87.35	6-8-1	97.24	91.4
6-9-1	97.86	89.31	6-9-1	98.41	92.15	**6-9-1**	**98.99**	**94.1**
6-10-1	94.51	85.79	6-10-1	96.24	91.9	6-10-1	99.1	89.5
6-11-1	98.4	92.5	6-11-1	94.65	84.5	6-11-1	93.8	92.5
6-12-1	97.26	91.99	6-12-1	95.5	79.73	6-12-1	97.34	85.54
6-8-7-1	92.06	91.63	6-9-7-1	97.52	82.5	6-9-7-1	98.44	82.4
6-8-8-1	98.54	82.91	6-9-8-1	95.61	85.18	6-9-8-1	93.5	83.12
6-8-9-1	**98.72**	**93.12**	6-9-9-1	92.76	84.62	6-9-9-1	98.94	90.36
6-8-10-1	99.25	89.93	6-9-10-1	96.1	80.43	6-9-10-1	97.45	86.72
6-8-11-1	97.62	82.14	6-9-11-1	91.7	90.5	6-9-11-1	98.34	74.19
6-8-12-1	93.19	80.94	6-9-12-1	95.6	87.13	6-9-12-1	97.29	85.26
6-8-9-7-1	97.32	84.36	**Winter + Spring**			**Spring + Summer**		
6-8-9-8-1	95.32	81.46	**Architecture**	**Training Accuracy%**	**Testing Accuracy%**	**Architecture**	**Training Accuracy%**	**Testing Accuracy%**
6-8-9-9-1	91.36	87.3	6-7-1	98.6	86.14	6-7-1	96.34	89.3
6-8-9-10-1	93.86	82.63	6-8-1	95.35	92.28	6-8-1	98.37	82.73
6-8-9-11-1	94.52	87.5	6-9-1	95.37	82.73	**6-9-1**	**98.73**	**94.65**
6-8-9-12-1	97.25	88.23	6-10-1	98.65	81.07	6-10-1	95.38	90.4
Autumn			6-11-1	99.4	91.35	6-11-1	96.86	86.2
Architecture	**Training Accuracy%**	**Testing Accuracy%**	6-12-1	96.89	76.8	6-12-1	96.48	85.4
6-7-1	96.1	90.7	6-8-7-1	97.4	85.2	6-9-7-1	97.2	84.39
6-8-1	**95.35**	**92.59**	6-8-8-1	95.96	81.89	6-9-8-1	96.55	83.76
6-9-1	96.18	89.34	6-8-9-1	98.42	82.51	6-9-9-1	98.94	86.39
6-10-1	94.24	84.37	6-8-10-1	96.73	89.34	6-9-10-1	97.63	84.73
6-11-1	97.1	90.35	6-8-11-1	98.05	83.4	6-9-11-1	97.59	87.93
6-12-1	96.38	83.18	6-8-12-1	98.91	81.3	6-9-12-1	96.38	81.28
6-8-7-1	97.17	87.36	**Summer + Autumn**			**Autumn + Winter**		
6-8-8-1	98.99	78.45	**Architecture**	**Training Accuracy%**	**Testing Accuracy%**	**Architecture**	**Training Accuracy%**	**Testing Accuracy%**
6-8-9-1	93.66	81.69	6-7-1	96.59	84.19	6-7-1	97.36	84.7
6-8-10-1	97.16	81.48	6-8-1	98.38	84.2	6-8-1	99.05	92.74
6-8-11-1	98.49	91.89	6-9-1	98.66	87.45	6-9-1	98.37	89.43

Winter			Spring			Summer		
Architecture	Training Accuracy%	Testing Accuracy%	Architecture	Training Accuracy%	Testing Accuracy%	Architecture	Training Accuracy%	Testing Accuracy%
6-8-12-1	96.26	86.3	6-10-1	95.99	89.49	**6-10-1**	**98.96**	**93.75**
x			6-11-1	99.64	94.2	**6-11-1**	**97.45**	**87.41**
			6-12-1	97.49	92.18	6-12-1	96.49	85.95
			6-11-7-1	95.73	93.61	6-10-7-1	97.89	90.58
			6-11-8-1	97.59	85.36	6-10-8-1	98.04	86.39
			6-11-9-1	98.56	89.63	6-10-9-1	98.57	87.53
			6-11-10-1	96.18	83.27	6-10-10-1	97.94	85.99
			6-11-11-1	98.42	90.59	6-10-11-1	97.83	89.73
			6-11-12-1	99.06	87.68	6-10-12-1	96.84	89.26

Table 5: Optimal Architecture of Each Segment

Segment	Architecture
Winter	6-8-9-1
Spring	6-9-1
Summer	6-9-1
Autumn	6-8-1
Winter+Spring	6-8-1
Spring+Summer,	6-9-1
Summer+Autumn,	6-11-1
Autumn + Winter	6-10-1

Fig. 5: Regression Plot of Winter

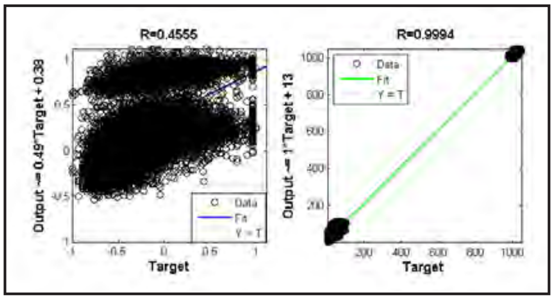


Fig. 6: Regression Plot of Spring

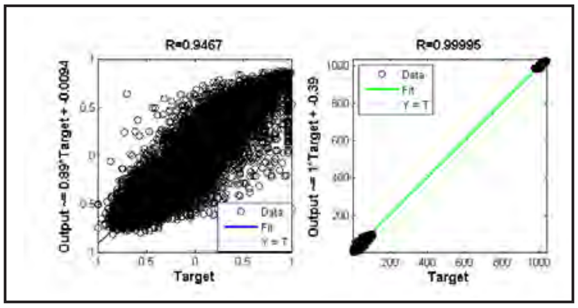


Fig. 7: Regression Plot of Summer

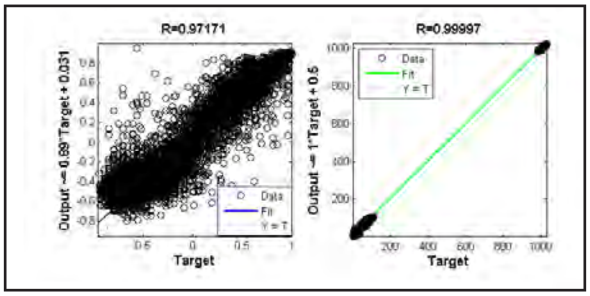


Fig. 8: Regression Plot of Autumn

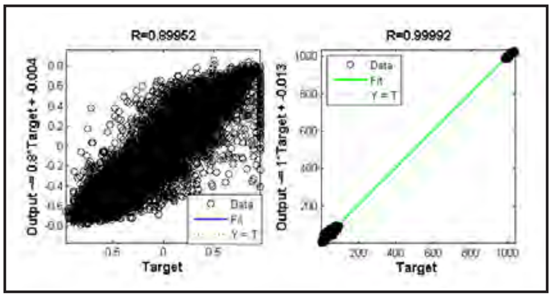


Fig. 9: Regression Plot of Autumn + Winter

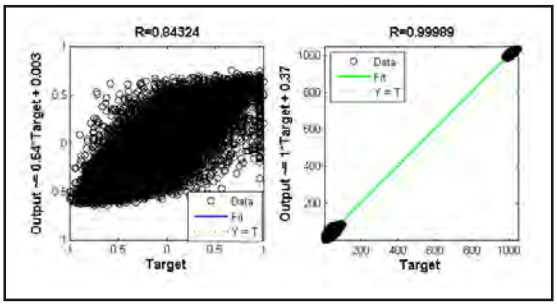


Fig. 10: Regression Plot of Spring + Summer

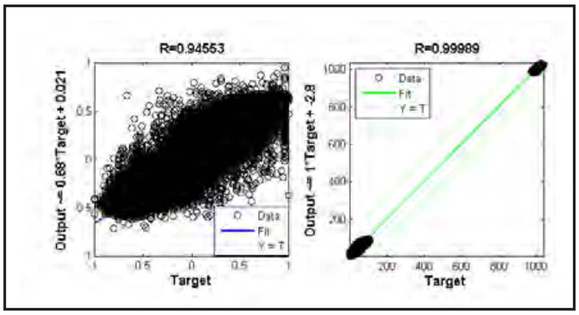


Fig. 11: Regression Plot of Winter + Spring

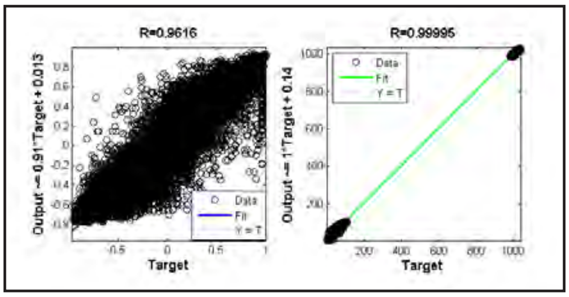
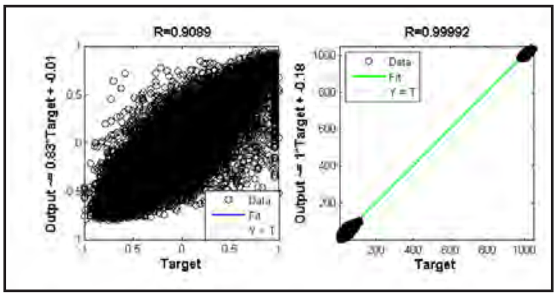


Fig. 12: Regression Plot of Summer + Autumn



Results

544 cases from the year 2008 and 2009 are considered in all the three experiments for forecasting weather. Fig. 13 shows the weight of similar cases in producing accurate result. It is observed from Fig. 13 that weight of similar cases monotonically decreasing with increasing k values; therefore closed similar cases keep higher significance in accurate prediction. The forecast accuracy is recorded for the three experiments as shown in Fig. 14. It is observed that the average accuracy of the proposed model is higher than that of simple CBR as well as segmented CBR. By using simple CBR and segmented CBR, the accuracy can't be improved even by using k nearest neighbours. The graph in fig. 15 shows the performance of simple CBR, segmented CBR and the proposed integration of CBR and NARXNN model for k equals 1 to 20. Fig. 16 also shows the variation in accuracy of the proposed model for k equals 1 to 20. The x axis denotes number of weighted most similar cases and the y axis denotes the accuracy level of the corresponding similar cases.

Fig. 13: Similar Case versus Weight

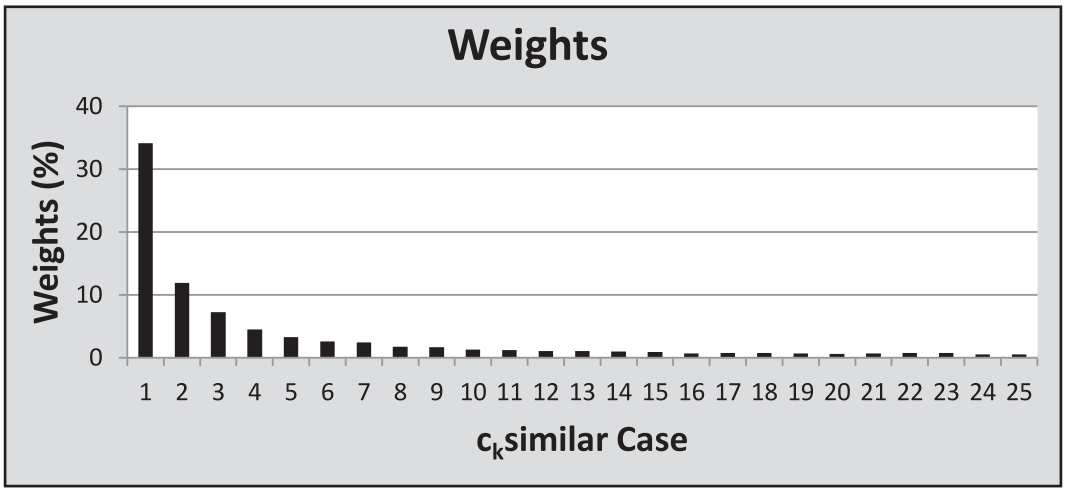


Fig. 14: Accuracy Comparison of Three Methods

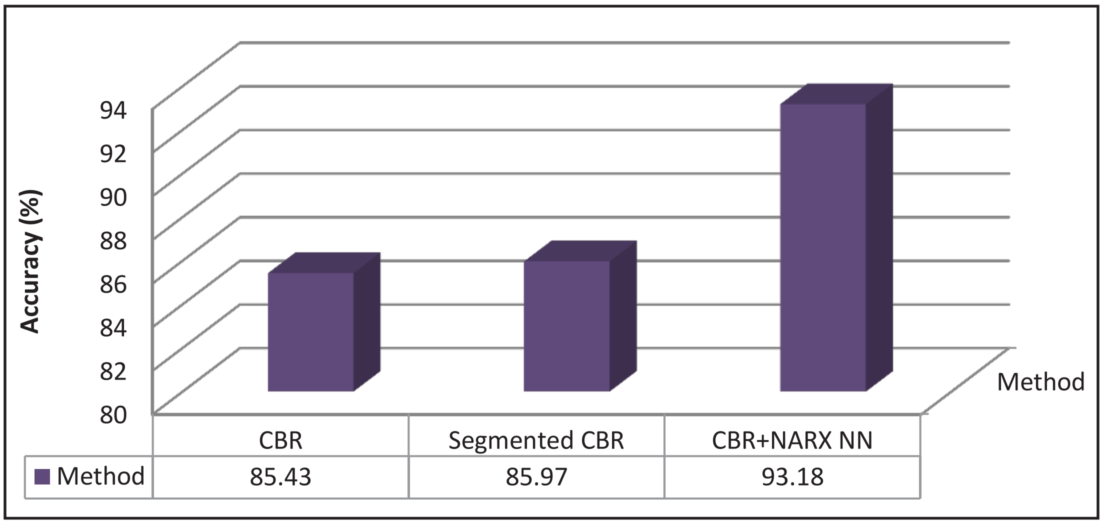


Fig. 15: Accuracy versus Number of k for Simple CBR, Segmented CBR and Proposed Model

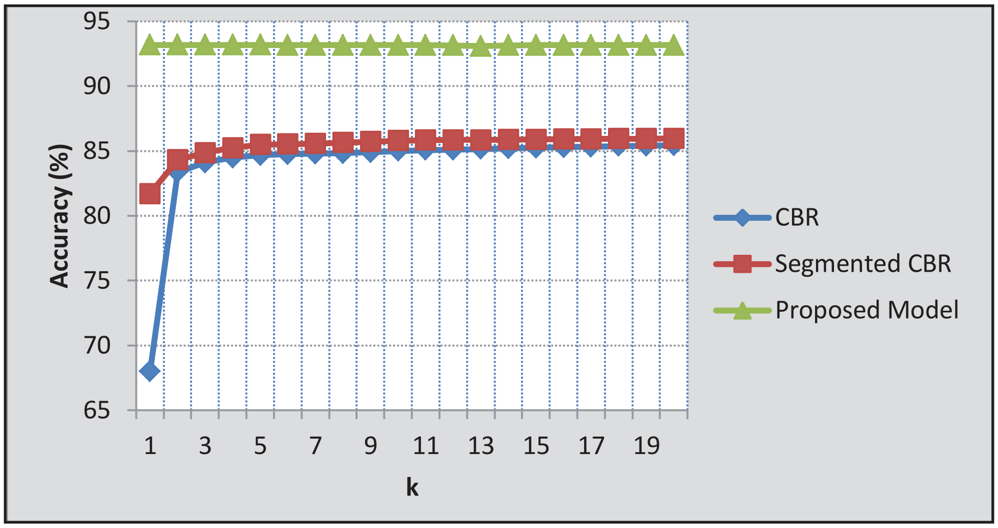


Fig. 16: Accuracy versus Number of k for Proposed Model

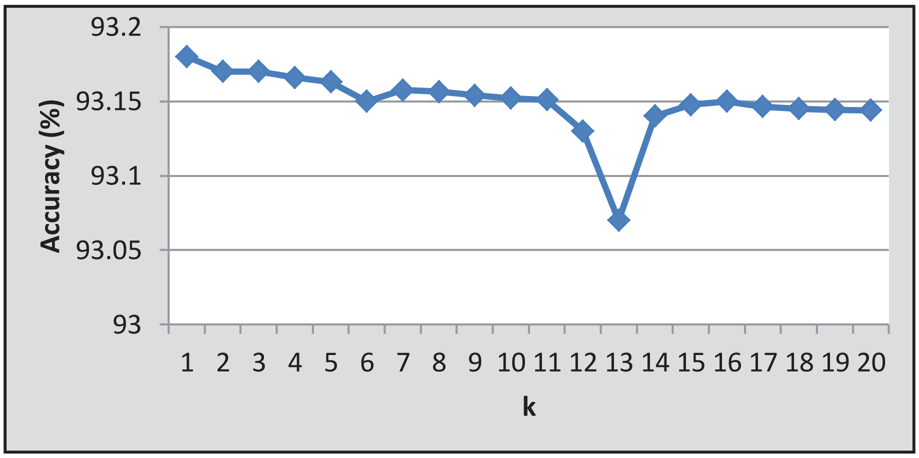
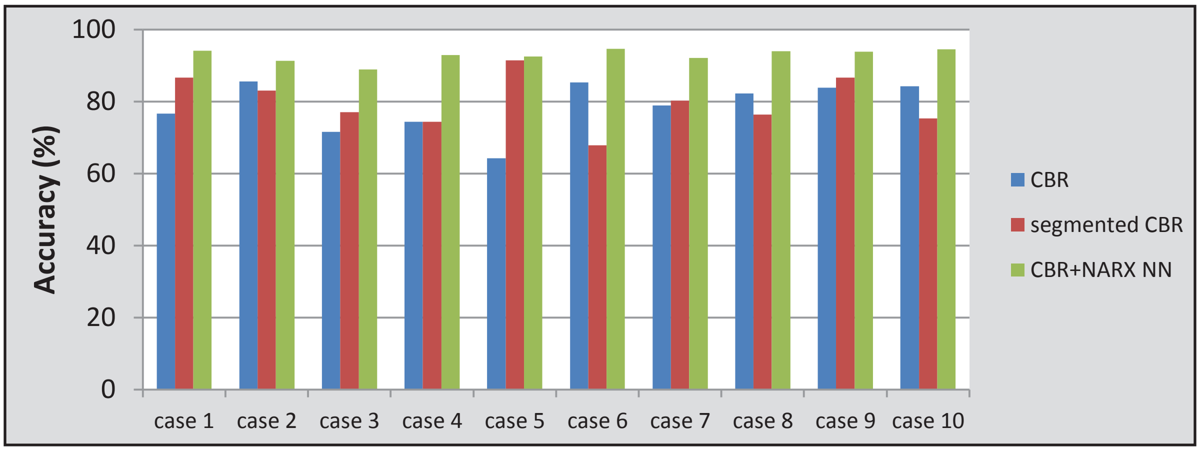


Fig. 17 shows the performance of the three methods for ten individual cases. For each individual case, the performance of the hybrid model is better than that of two CBR methods. The x axis denotes individual cases and the y axis denotes the accuracy of the corresponding cases.

Fig. 17: Accuracy of Individual Cases by Three Methods



Discussions

In this work it has been investigated whether the hybridisation of CBR with NARXNN enhances the accuracy of the prediction of weather attributes as compared to CBR methods with Euclidean distance. The proposed method uses NARXNN to replace Euclidean distance and to capture the generalised knowledge and weather dynamics of meteorological data. Experimental results show that CBR-NARXNN can outperform both the simple CBR and segmented CBR. In the third experiment, NARXNN architectures used are not optimal as delay lines and other performance parameters other than number of layers and number of nodes in each layer are not optimised. The segmented case base is only used in second and third experiments. The detail of how the performance of the network architecture varies with varying number of layers or neurons is shown. Regression plots are shown to have better understanding of the data in the training phase. The mean square error for four non-overlapping and four overlapping test cases are shown to have a better understanding of comparison of the three approaches. The weights shown in Fig. 13 are calculated by five-folded cross validation of training data to produce best prediction using standard CBR model. It should be noted that the temperature and dew point are measured in Fahrenheit scale, pressured is measured in Pascal, wind speed is measured in knot and visibility is measured in kilometre.

Conclusion

This paper gives an overview about weather prediction and its approaches. It also highlights the existing different uses of CBR in weather prediction and others. This work proposes an innovative way of capturing weather dynamics with NARXNN for use in the CBR approach. The integration of NARXNN into CBR is made to enhance the accuracy of the CBR in predicting one day ahead multiple weather attributes. Experimental results demonstrate that the use of intelligent agent (NARXNN) has improved the accuracy of the prediction method over the other two methods. In fact, the proposed method has performed much better than both simple CBR and segmented CBR methods. The main contribution of NARXNN is that it has the strength in learning the linear and non-linear relationships of the data as well as the dynamic behaviour of the system over a period of time. This is required as local weather conditions may change by the passing years because of other environmental effects. For example, a newly constructed dam, or a destructed forest may change local effects. So, only simple historical data may be misleading.

All most all the works in the literature on forecasting of weather are related to prediction of only single or two attribute(s) at a time. The proposed approach provides a simple way for understanding the complex relationships among the multiple weather-attributes. Moreover, predicting multiple weather attributes at the same time reduces the time complexity as compared to predicting one attribute at a time. The proposed model can be used as a local weather forecaster irrespective of number of attributes. The accuracy of the proposed method can be improved by introducing a better way of imparting the knowledge of weather dynamics on how the weather of a year influences the weather of the subsequent years or by introducing some other intelligent data mining tools.

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