Hybrid ARIMA-HyFIS Model for Forecasting Univariate Time Series

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ABSTRACT
In this paper, a novel hybrid model for fitting and forecasting a univariate time series is developed based on ARIMA and HyFIS models. The linear part is fitted using ARIMA model whereas the non-linear residual is fitted using HyFIS model. Clustering technique is used to determine the number of inputs and the membership functions of the HyFIS model. The hybrid model is applied to the wind speed data. The result is analyzed and compared on the basis of standalone ARIMA, standalone HyFIS and for the hybrid ARIMA-HyFIS model.

General Terms
ARIMA, ANFIS, DENFIS, HyFIS, Hybrid Algorithm

Keywords
ARIMA-HyFIS, ARIMA, HyFIS, Fuzzy Inference System, Clustering.

1. INTRODUCTION
Modeling and forecasting wind speed data is important to forecast weather. It is also significant to model the wind speed data to forecast the energy produced by wind mills. In this paper, a novel two stage hybrid ARIMA-HyFIS model for forecasting wind speed is developed. The wind speed data is taken using buoy (station 42059) by NDBC at the latitude **15.054 N** and longitude **67.472 W** for the whole of year 2013 [1]. The data are modeled first by ARIMA followed by HyFIS and then by hybrid ARIMA-HyFIS. The results are discussed in detail.

Throughout this paper the meaning of a quarter is 3 months starting from January not economic quarter which normally begins at April. The rest of the research is organized as follows. In section 2, literature review is presented. Section 3 describes the basic concepts of HyFIS model and data preparation using cluster analysis. In section 4, the wind speed data is applied to different models and the results obtained are discussed. Section 5 concludes this paper.

2. LITERATURE REVIEW
Box and Jenkins [2] developed the autoregressive moving average to predict time series. There exists a vast literature for forecasting a univariate time series model based on neuro-fuzzy inference system. A fuzzy ARIMA model for forecasting foreign exchange market is presented in [3]. A hybrid ARIMA and neural network approach for forecasting time series is presented in [4]. "Al-Fuhaid et al." developed a neural network based short term load forecasting in Kuwait [5]. "Che et al." developed a hybrid model for forecasting short term electricity prices based on ARIMA and support vector regression [6]. Different hybrid forecasting approaches are evaluated in [7]. "Chengqun Yin et al." forecasted short term load based on hybrid neural network model [8].

Fuzzy rule based system based on learning from example was developed by Wang and Mendel [9]. Jang developed a neural network based fuzzy inference system which later on named as ANFIS [10] [11]. ANFIS stands for adaptive network based fuzzy inference system. ANFIS is a hybrid model in the sense it uses both neural network and fuzzy logic. Kim and Kasabov developed a hybrid model which later on denoted by HyFIS [12]. The difference between ANFIS and HyFIS is discussed in the next section. Kasabov and Song developed a dynamically evolving neural network model which later on denoted by DENFIS [13]. DENFIS stands for dynamically evolving network based fuzzy inference system. Later on evolutionary algorithms are used to tune the parameters of the hybrid neuro-fuzzy inference systems [14].

In [15], a hybrid model is presented to forecast the short-term electricity load in Indonesia based on ARIMA-ANFIS architecture. "Ren Ye et al." developed a hybrid ARIMA-DENFIS method for forecasting wind speed [16].

3. OVERVIEW OF HyFIS MODEL AND DATA PREPARTION

3.1 Overview of HyFIS Model
The architecture of HyFIS model is presented in this section. Fig. 1 describes the architecture of a HyFIS model in which three membership functions are used for the two inputs. In this model, nine rules are used. In this figure a square node denotes an adaptive node and circular node denotes a fixed node. The difference between the ANFIS and HyFIS models are given below.

- The membership function can take any shape in ANFIS whereas in HyFIS the membership functions are only Gaussian. Since HyFIS uses Gaussian MF, only two parameters need to be optimized i.e. mean and variance of the membership function.
- The ANFIS uses Takagi Sugeno Kang model [17] (TSK) in the consequent part whereas HyFIS model uses a Mamdani model [18]

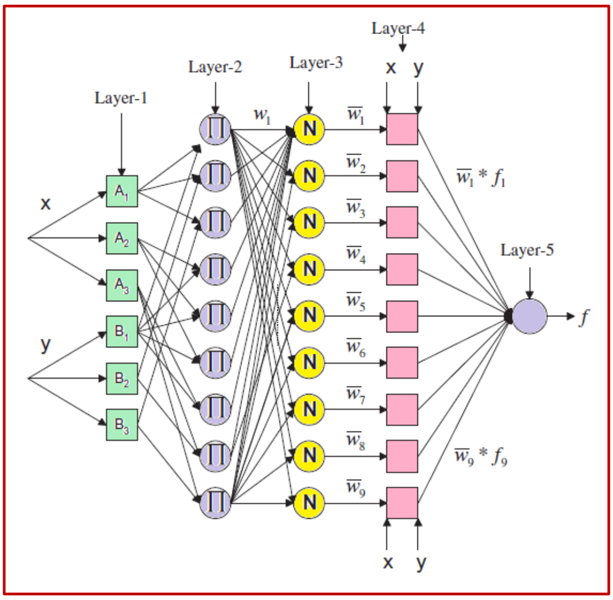

Fig 1: Two input nine rule HyFIS architecture

Layer 1 is the antecedent node in which inputs are applied. Layer 2 is the multiplication node and it simply multiplies the input signal and calculates the firing strength of each rule. Layer 3 is the rule node which calculates the relative firing strength of each rule. Layer 4 is the consequent node where consequent parameters are calculated and de-fuzzification takes place. Layer 5 is the output node which sums over all of the input and calculates the output. The learning of structure and parameters is a supervised learning method using gradient descent-based learning algorithms. The parameters of the square node are determined using supervised learning technique with help of training data. The training data consists of input and output parameters of the system to be identified.

3.2 Data Preparation Using Clustering

The wind speed data is taken for the whole of the year 2013 with a sampling time of 10 minutes. The analysis is carried out in the following way. The data as whole of a year is considered followed by four quarter data. For this purpose the whole of the year data is split into four quarters. In order to determine the number of inputs for the HyFIS model, the data is clustered and the number of clusters is used as number of inputs to the HyFIS model. The number of membership function in each case is set equal to the number of clusters available in the data set. The fitted ARIMA model *p,d,q* are summarized in table 1. Figures 2-7 depict cluster obtained for different cases. ARIMA model is fitted using the R language [19].

Table 1. Order of ARIMA models fitted for each case

Case	order (p,d,q)	θ	ϕ
Q1 data	(3,1,2)	0.48 0.18 0.10	-0.93 -0.015
Q2 data	(4,1,2)	-0.13 0.50 0.19 0.08	-0.33 -0.58
Q3 data	(5,1,3)	0.014 -0.44 0.72 0.34 0.12	-0.51 0.48 -0.97
Q4 data	(4,1,4)	-0.39 0.05 0.67 0.02	-0.15 -0.3 -0.69 0.32
Entire year	(6,1,3)	-0.22 0.15 0.36 0.15 0.05 0.01	-0.28 -0.27 -0.33

The order and the coefficients of the ARIMA model fitted for each of the five cases is tabulated in table 1. The data and the residuals of the ARIMA model is clustered using three different clustering techniques namely k-means clustering [20], fuzzy C-means clustering [21] [22] and subtractive clustering [23]. The results of the clustering are summarized in table 2.

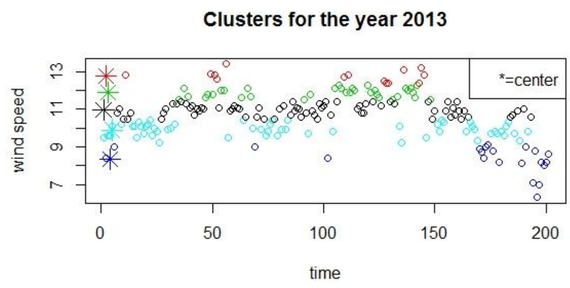

Fig 2: Five clusters for the entire data

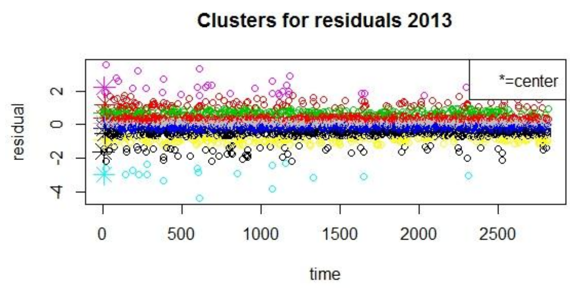

Fig 3: Ten clusters for the residual of year case

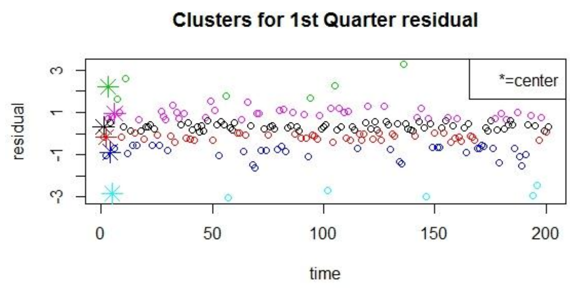

Fig4: Six clusters for the residual of Q1

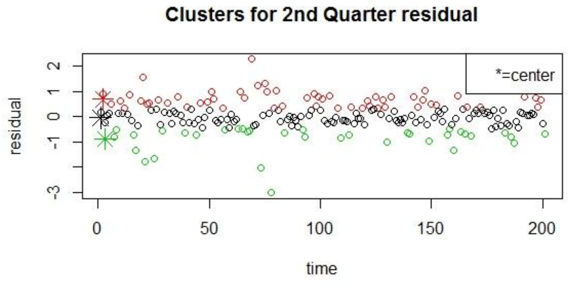

Fig 5: Three clusters for the residual of Q2

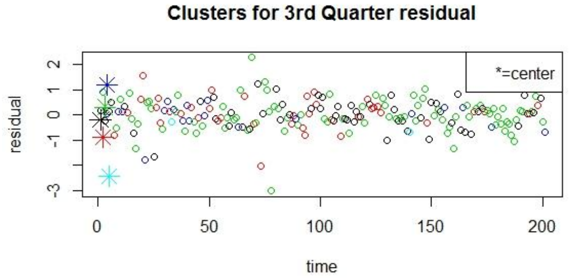

Fig 6: Five clusters for the residual of Q3

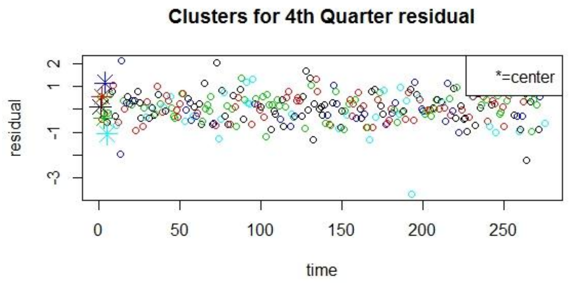

Fig 7: Five clusters for the residual of Q4

Table 2. Comparison of different clustering techniques

case	K-means Clustering		Fuzzy C-mean Clustering		Subtractive Clustering	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
Q1 data	0.612	0.521	0.692	0.598	0.512	0.421
Q1 residual	0.721	0.597	0.721	0.674	0.631	0.543
Q2 data	0.591	0.497	0.667	0.574	0.491	0.401
Q2 residual	0.647	0.589	0.712	0.657	0.557	0.519
Q3 data	0.609	0.514	0.698	0.672	0.527	0.453
Q3 residual	0.649	0.573	0.687	0.659	0.543	0.475
Q4 data	0.631	0.498	0.736	0.631	0.549	0.487
Q4 residual	0.641	0.574	0.715	0.659	0.558	0.438
Entire year	0.713	0.690	0.759	0.712	0.631	0.573
Entire year residual	0.871	0.801	0.931	0.879	0.819	0.712

From table 2, it is clear that K-means clustering produces a moderate MAE and lower RMSE than other techniques. The other techniques produce a result that is comparable with the K-means clustering. The computing time for K-means clustering is lesser than other techniques and hence it is chosen for this analysis. Based on K-means clustering the number of inputs and the number of membership functions are determined and they are summarized in table 3. It is to be noted that the number of clusters is equal to the number of inputs and also equal to the number of membership functions for each case.

Table 3. Number of clusters and inputs for each case

Case	Number of clusters	Number of inputs	Number of member-ship functions for each variable
Q1 data	3	3	3
Q1 residuals	6	6	6
Q2 data	4	4	4
Q2 residuals	3	3	3
Q3 data	5	5	5
Q3 residuals	5	5	5
Q4 data	4	4	4
Q4 residuals	5	5	5
Entire year	5	5	5
Entire year residuals	10	10	10

The definition of error measures used to evaluate this model is given below.

$$\text{MAE}= E\left[\left|\hat{x}(t)-x(t)\right|\right]$$

$$\text{MAPE}= E\left[\left|\frac{\hat{x}(t)-x(t)}{x(t)}\right|\right]\times 100\%$$

$$\text{RMSE}= \sqrt{E\left[(\hat{x}(t)-x(t))^2\right]}$$

4. EXPERIMENTAL RESULTS

Five cases are studied in this work as shown in table 1. In each case an ARIMA model, a HyFIS model and a hybrid ARIMA-HyFIS model is applied. The testing results are shown in the following tables.

Table 4. Error measures for 3 hour ahead forecasting

Case		ARIMA	HyFIS	ARIMA-HyFIS
Q1	MAE	0.11	0.13	0.11
	MAPE	11.33	13.75	11.54
	RMSE	0.13	0.15	0.13
Q2	MAE	0.09	0.10	0.08
	MAPE	12.33	15.73	12.05
	RMSE	0.12	0.14	0.10
➢ Q3	MAE	0.09	0.12	0.11
	MAPE	11.73	14.75	11.98
	RMSE	0.11	0.16	0.13
Q4	MAE	0.09	0.14	0.09
	MAPE	12.09	15.19	11.87
	RMSE	0.12	0.16	0.12
Entire year	MAE	0.12	0.15	0.11
	MAPE	12.87	16.89	11.06
	RMSE	0.14	0.17	0.12

In Table 4, error measures of 3 hour ahead forecasting results are summarized. Table 5 summarizes the error measures of 6 hour ahead forecasting. Table 6 summarizes the error measures of 9 hour ahead forecasting. Figure 8 to figure 12 depict the ARIMA, HyFIS and ARIMA-HyFIS model used for 3 hours ahead forecasting for different cases (In figures only 100 minute ahead forecasting is shown for the sake of clarity of figures). Figure 13 shows MAPE versus period of forecasting for 3rd quarter in which *ARIMA model has outperformed ARIMA-HyFIS model.*

Table 5. Error measures for 6 hour ahead forecasting

Case		ARIMA	HyFIS	ARIMA-HyFIS
Q1	MAE	0.15	0.17	0.14
	MAPE	18.23	21.85	16.78
	RMSE	0.17	0.19	0.16
Q2	MAE	0.15	0.14	0.11
	MAPE	19.45	23.83	18.07
	RMSE	0.18	0.17	0.15
➢ Q3	MAE	0.13	0.18	0.14
	MAPE	17.83	21.75	18.94
	RMSE	0.16	0.21	0.17
Q4	MAE	0.14	0.19	0.14
	MAPE	19.08	23.09	17.98
	RMSE	0.19	0.23	0.17
Entire year	MAE	0.18	0.21	0.15
	MAPE	18.77	23.79	17.76
	RMSE	0.21	0.25	0.19

Table 6. Error measures for 9 hour ahead forecasting

Case		ARIMA	HyFIS	ARIMA-HyFIS
Q1	MAE	0.17	0.19	0.16
	MAPE	27.54	30.65	25.18
	RMSE	0.21	0.23	0.19
Q2	MAE	0.16	0.18	0.15
	MAPE	28.75	31.87	26.17
	RMSE	0.20	0.22	0.18
➢ Q3	MAE	0.14	0.21	0.16
	MAPE	25.18	29.86	26.98
	RMSE	0.17	0.25	0.19
Q4	MAE	0.17	0.21	0.13
	MAPE	26.78	31.07	24.87
	RMSE	0.22	0.26	0.18
Entire year	MAE	0.23	0.25	0.18
	MAPE	28.77	32.79	25.16
	RMSE	0.28	0.31	0.21

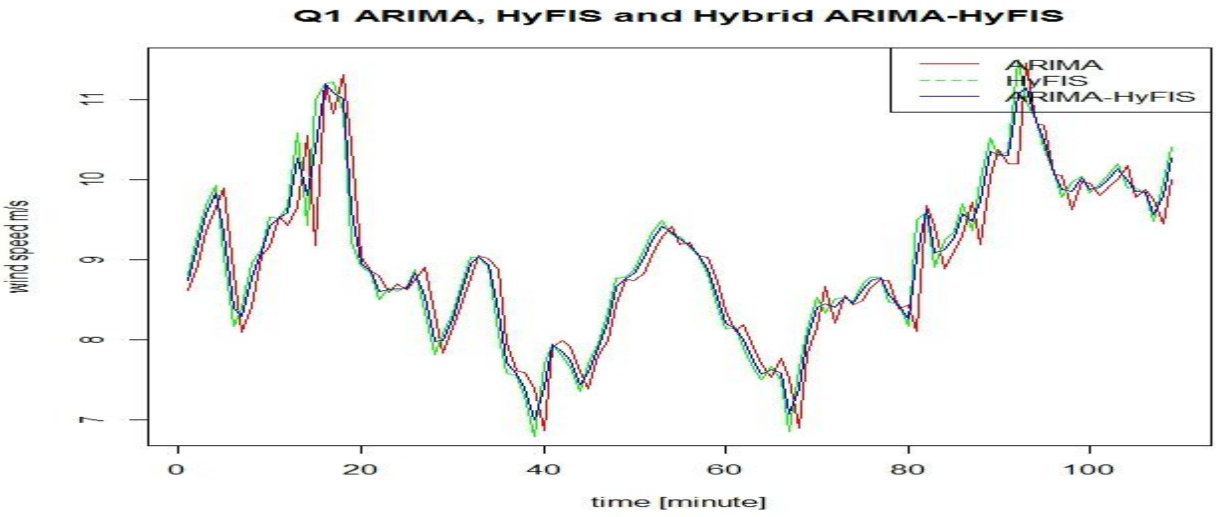

Fig 8: ARIMA-HyFIS model for three hours ahead forecasting for first quarter of 2013

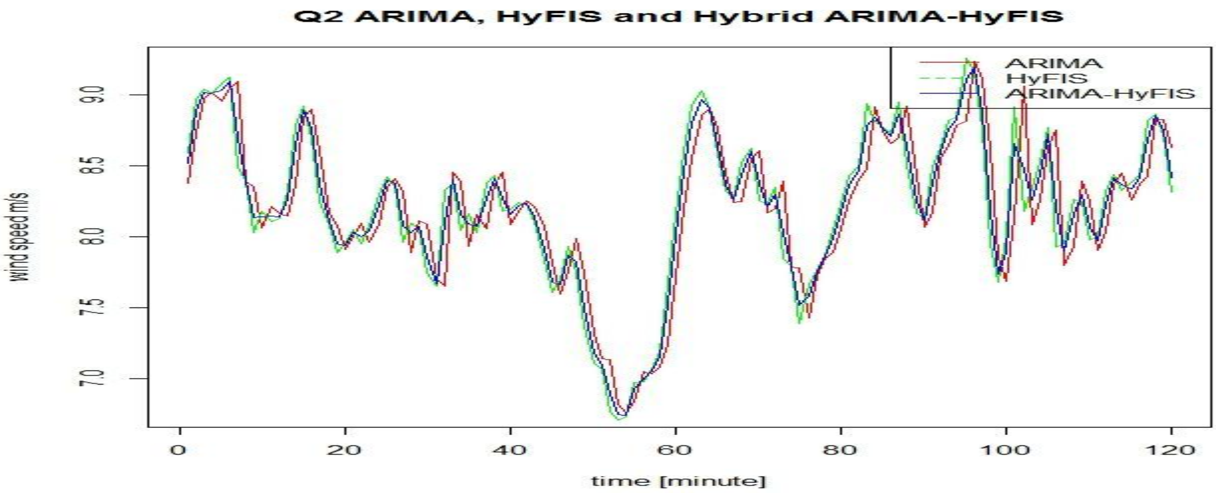

Fig 9: ARIMA-HyFIS model for three hours ahead forecasting for second quarter of 2013

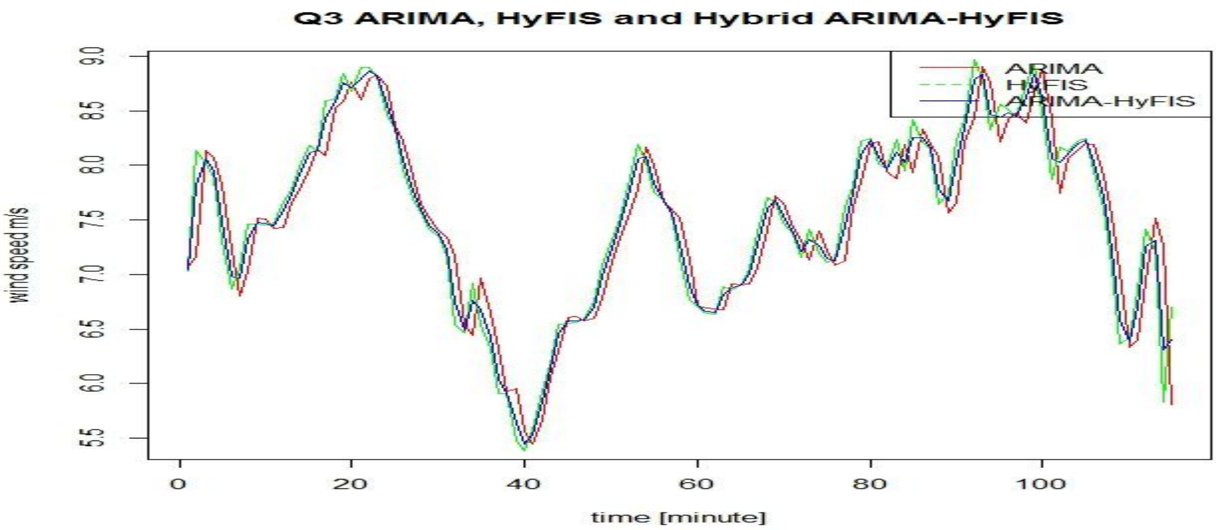

Fig 10: ARIMA-HyFIS model for three hours ahead forecasting for third quarter of 2013

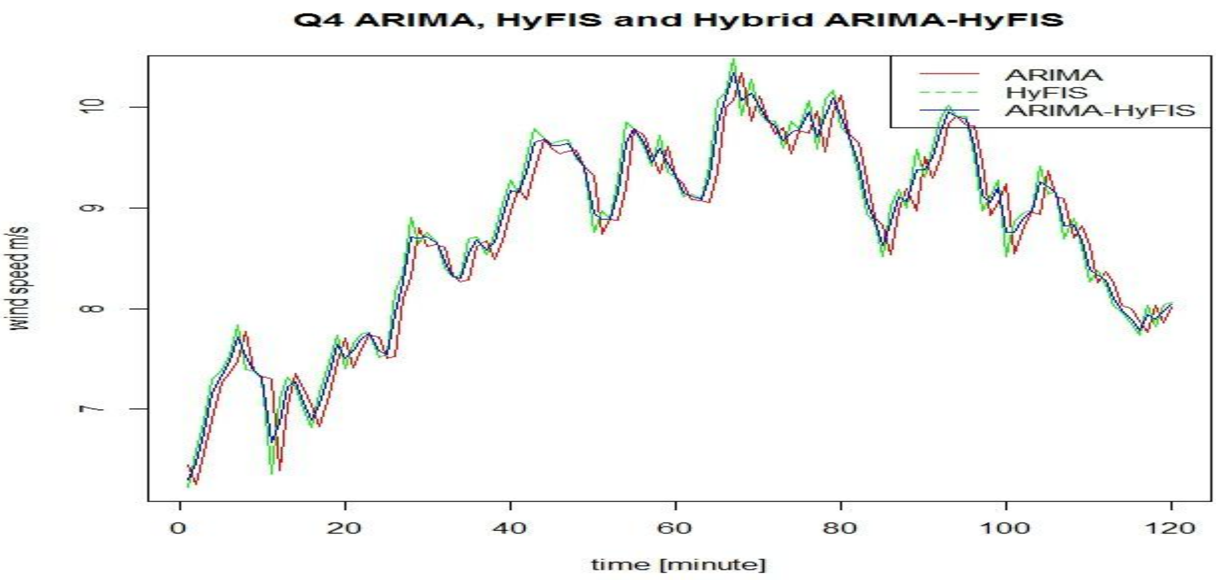

Fig 11: ARIMA-HyFIS model for three hours ahead forecasting for fourth quarter of 2013

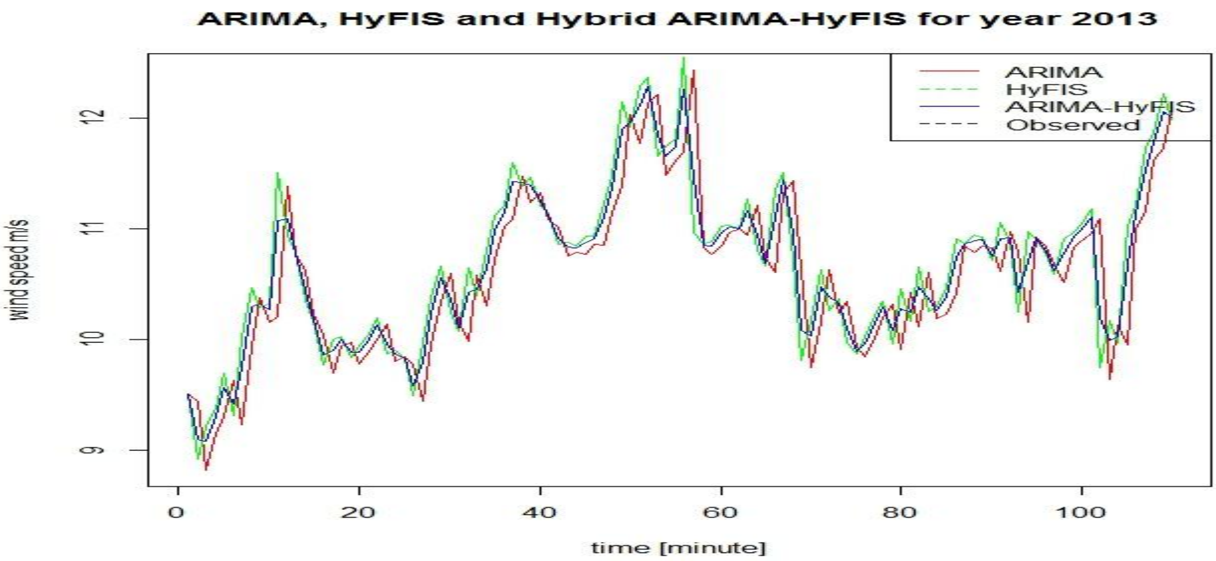

Fig 12: ARIMA-HyFIS model for three hours ahead forecasting for the entire year of 2013

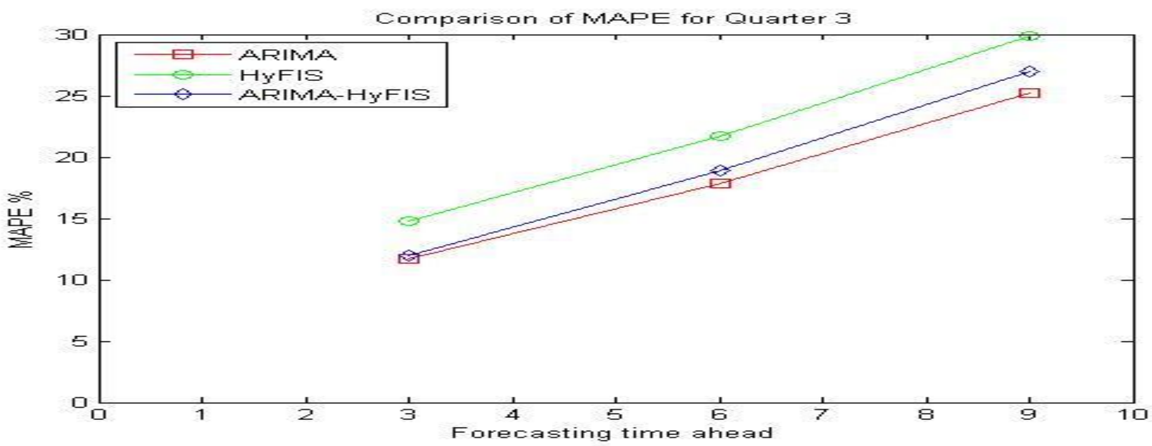

Fig 13: MAPE for third quarter

5. CONCLUSION

This paper proposed a new hybrid ARIMA-HyFIS model for forecasting time series data. This model uses clustering technique to determine the number of inputs that are applied to the HyFIS model. The proposed model has been evaluated with NDBC wind speed data. The results are tabulated as well as pictorially represented. The proposed ARIMA-HyFIS model has outperformed the conventional ARIMA and HyFIS model in most of the cases. But in ***Q3, the ARIMA model*** has outperformed the hybrid ARIMA-HyFIS model. It is planned to tune the membership function's parameters using evolutionary algorithms.

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