

# Time Series Modeling of Adani Power & Tata Power Closed Prices based on Adaptive Neuro-fuzzy Inference System-Wavelet Model

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## Abstract

This study integrates wavelet transforms with the Adaptive Neuro-Fuzzy Inference System (ANFIS) to forecast the stock prices of Tata Power and Adani Power. Using Daubechies wavelet (Db8) at level 3, the data were decomposed to capture complex patterns. Performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE). In the test phase, the ANFIS- Wavelet model improved RMSE by 5.89%, MAE by 8.35%, and MSE by 11.44% for Tata Power, and RMSE by 6.34%, MAE by 0.38%, and MSE by 12.27% for Adani Power compared to the standard ANFIS model. These results highlight the superior accuracy of the hybrid approach for time series forecasting, offering better insights for decision-making in financial analysis.

**Keywords**-Wavelet Transform, Stock Price Forecasting, Db8 Wavelet, ANFIS, Closed Prices, Time Series Analysis

## 1. Introduction

Forecasting helps to predict the approximate future values. In case of time series forecasting, it uses both historical and current information to predict the future values. It is important now days to develop such models which predict accurate or near to accurate values so that the investors may avoid losses in the stock market. Forecasting time series is practiced in various fields like Economics, Meteorological Sciences, Natural Sciences, Business and Engineering. There are various forecasting methods like ARMA (Autoregressive Moving Average) & its extension ARIMA (Autoregressive-Integrated Moving Average), moving average, exponential smoothing, linear forecasting, Neural Networks, ANFIS (Adaptive Neuro Fuzzy Inference System), etc, which are employed to generate outcomes by analyzing the historical data [1,6,11,12,22]. These above models are divided into two types, stationary and non-stationary. Statistics like variance and mean remain never change in stationary models, while in non-stationary models, these features change on time [17]. Generally, the extreme fluctuations with high frequency make the real-time series data non-stationary

Fourier transform is most widely used tool for signal processing. It is a mathematical tool for transforming the time domain signal to frequency domain. Fourier transform utilizes sinusoidal waves as basis functions which extend from  $-\infty$  to  $\infty$ . So, it describes only spectral information of the signal and does not unveil its time localization. It is localized in only one domain either time or frequency hence it is not useful for non-stationary signals [21].

In 1946, D. Gabor was the first to identify the limitations of the Fourier transform in time-frequency analysis[5]. He used the idea of a window function to construct an alternative transform. The term "*Short-Time Fourier transform*" (STFT) or "*Windowed Fourier Transform*" refers to this time-frequency analysis technique (Fig.1). In STFT, we first choose the appropriate segment of the input signal before performing the Fourier transform on it. The disadvantage of STFT is that it uses a single window for all frequencies, resulting in the same level of analysis resolution over the whole time-frequency plane. Heisenberg's uncertainty principle dictates that a window with a big width offers good frequency resolution but poor time resolution, while one with a small width offers good time resolution but poor frequency resolution. As a result, we are unable to simultaneously obtain strong frequency resolution and good timing.

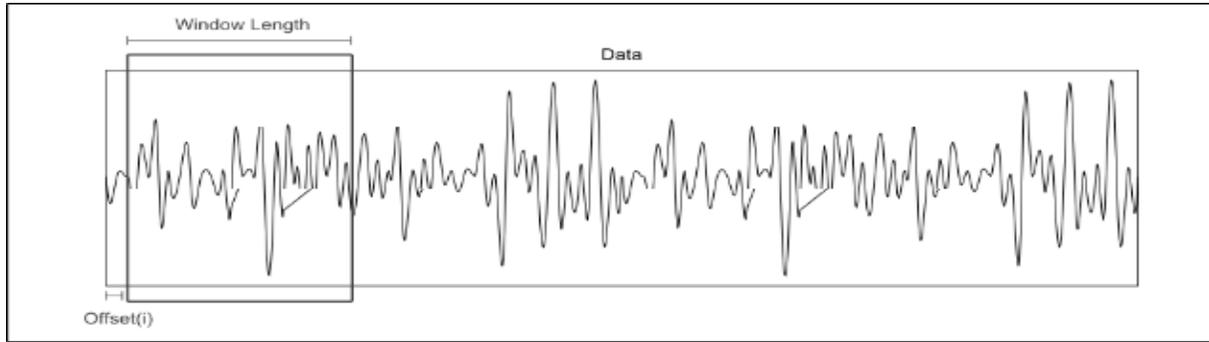


Fig. 1 (Short Time Fourier Transform)

There is some Fourier analysis which are ideal for studying stationary data but not useful for transient events, so to overcome that, wavelets were introduced. In time series analysis, a wavelet transform is therefore a particularly useful tool. Wavelet transform can be considered as a refinement of Fourier transform [21]. The idea of multiresolution was put forth by Meyer and Stephane Mallat in 1988 [14]. The compact support orthogonal wavelet was created using a systematic manner by Ingrid Daubechies in the same year [3]. In 1989, *Fast Wavelet Transform* was launched by Mallat. With the appearance of this fast algorithm, the wavelet transform had numerous applications in the signal processing field [15]. Numerous applications, including transmitting waves, data compression, signal analysis, processing images, recognizing patterns, and discontinuity detection as well as in applied and pure mathematics have demonstrated the effectiveness of wavelets [10].

This paper emphasis on the forecast of Tata Power & Adani Power (leading power generation companies) daily closed prices. For the welfare of nations and the growth of their economies, power is one of the most important elements of infrastructure. For India's economy to grow steadily, there needs to be a sufficient infrastructure for supplying it with power. One of the most globally diverse energy sectors is found in India. The power sector is extremely important to the GDP of the nation, India is the third largest producer of electricity in the world [7]. India is currently investing extensively in the power sector to meet its rising demand for electricity. Power price variations can have a significant impact on a nation's economy [4]. Time series are transformed into constituent series by wavelet transforms, which exhibit more stable variance and allow for more accurate prediction. For this reason, the wavelet transform is used. We use power sector stock market data from India for this purpose.

### 1.1 Wavelet Analysis

A function  $\Psi(x) \in L^2(R)$  is called wavelet if it satisfies the following properties:

1.  $\int_{-\infty}^{\infty} \Psi(t) dt = 0$
2.  $\int_{-\infty}^{\infty} |\Psi(t)|^2 dt < \infty$
3.  $C_{\Psi} = \int_{-\infty}^{\infty} \frac{|\hat{\Psi}(w)|^2}{w} dw < \infty ;$

where  $\hat{\Psi}(w)$  is the Fourier transform of  $\Psi(x)$  and  $C_{\Psi}$  being the admissibility constant [21,25].

Basically, wavelets are a family of functions created by translating and distorting a single function  $\Psi(x) \in L^2(R)$  known as *Mother wavelet* (where the scaling function is called *Father Wavelet*) [21].

The family of wavelets  $\Psi_{j,k}(x)$  are defined as,

$$\Psi_{j,k}(x) = |a|^{-1/2} \Psi\left(\frac{x-k}{j}\right); a, b \in \mathbb{R}, a \neq 0$$

where  $j$  is a scaling parameter and  $k$  is translation parameter [21].

Wavelet transform is a systematic and well-developed mathematical tool that decomposes a function or signal into wavelet basis functions. Wavelet transformation indeed proves to be an effective tool to decompose time series into different level of frequency [19]. The DWT, or discrete wavelet transform, is a useful tool for time series analysis since it displays a time series by means of the coefficients connected to specific scales. The input signal  $f(t)$  is divided into several resolution scales after applying the DWT on it. For the use of the wavelet transform, there are some software available. We make use of MATLAB's wavelet toolbox. When a signal is subjected to DWT, the wavelet coefficients must be gained; from given coefficients the signal's two halves are fabricated. A low-frequency or smoothed part of the signal is an approximation, and a high-frequency or detailed part of the signal is the other. The fine structure of the signal is preserved by the approximation component. There are different wavelets to use but Daubechies wavelet (Fig.2) is best fitted for our time series data. So, in this very paper, we used db8 level three which has the lowest error of all the wavelets. (db2, db4, db6, db8, db10) evaluated for our data set.

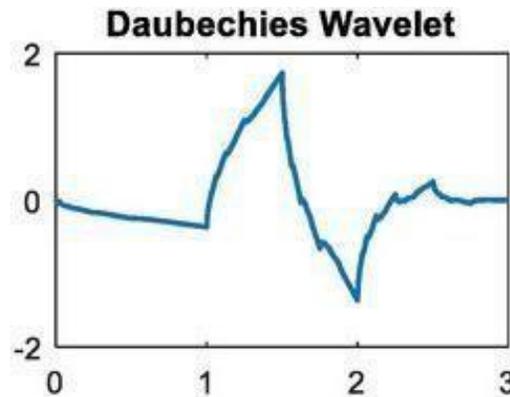


Fig. 2 Daubechies Wavelet (Pothisarn et al. 2020)

### 1.2 ANFIS (Adaptive Neuro Fuzzy Inference System)

One of the most popular and effective techniques for fuzzy logic and fuzzy set modelling is the fuzzy rule, which was first introduced by Zadeh [26]. Sugeno and Yasukawa in 1993 defined fuzzy-rule modelling as a qualitative modelling technique that describes system behavior using a natural language [23]. The current combination of fuzzy logic and neural networks allows for the development of a novel study called the adaptive neuro-fuzzy inference system (ANFIS). The computational process depends on the neural network's ability to learn on its own and the fuzzy inference system's language transparency so, it incorporates both neural network and fuzzy system advantages [9]. One of the major advantages of ANFIS over convectional modelling is its capacity to manage large amounts of data in nonlinear and dynamic systems, especially in situations when a complete knowledge of their physical linkages is not yet reached [18]. Data categorization, computer vision, database management, information retrieval, and autonomous control of signal processing are now all included in the expansion of ANFIS [8]. An equivalent class of adaptive network to FIS is ANFIS. Using the particular input output data, either a back-propagation algorithm or a hybrid learning algorithm (a hybrid combination of the least-squares method and backpropagation) is used in ANFIS to tune or alter the membership function parameters [16]. The process of modifying values in a fuzzy way is known as fuzzy modelling. Due to its tolerance to environmental changes, fuzzy inference system (FIS) implements fuzzy modelling on an input-output system with a collection of if-then rules [8], which offers advantages over other conventional mathematical approaches [24]. However, it is asserted that there is no accepted technique for formulating fuzzy rules and fine-tuning membership functions (MFs). In order to train the fuzzy inference system based on data, Jang presented an

adaptive network-based fuzzy inference system (ANFIS) in 1992. ANFIS has successfully demonstrated its best ability to handle ambiguity and has been extensively employed in forecasting methodologies. It achieves this by fusing fuzzy logic with neural networks. In order to calculate the temperatures of rooms indifferent residential structures, Alasha'ary et al. in 2009 developed a neuro-fuzzy model, which demonstrated the predictability with a satisfactory level of accuracy [2]. Of all neural networks, ANFIS has unparalleled accuracy of the prediction, as shown by Singh, Sinha, and Singh [16]. To anticipate electric loads, Ying and Pan in 2008 proposed ANFIS. This model outperformed others, such as hybrid ellipsoidal fuzzy systems, ANN, SVM, and regression [13].

## 2. Framework and Methodology

We have used MATLAB for ANFIS for the forecasting of data to observe some results. Since large sample sizes of 100 or more are optimal for the wavelet-based forecasting method [11], so we take a large amount of data of Tata Power & Adani Power from the Indian Stock Market. The data is collected from Yahoo Finance site (<https://finance.yahoo.com>) over a period of 1<sup>st</sup> Jan 1996 to 18<sup>th</sup> Oct 2021 for Tata Power and 20<sup>th</sup> Aug 2009 to 24<sup>th</sup> Dec 2022 for Adani Power. The two sets of data are separated into training and testing phases. We create prediction models for every decomposed part of the original series throughout the training phase. In the testing phase, we compare the predicted values with the actual values using the forecasting models that have been constructed. The proposed technique (Fig 2.1) consists of the following steps:

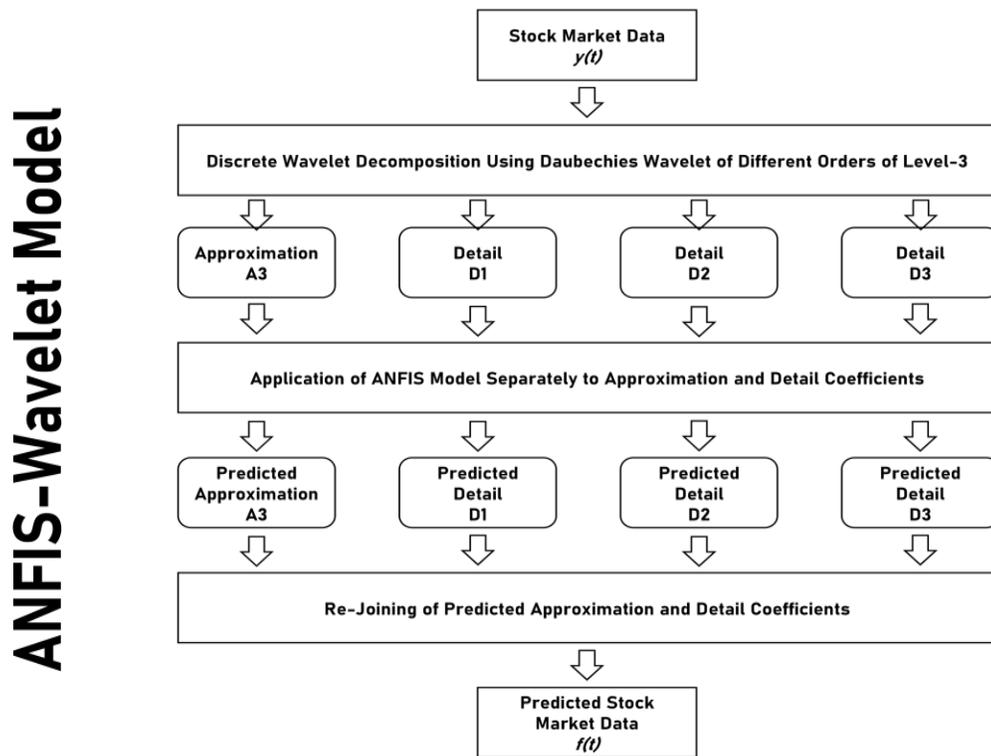


Fig. 2.1 (Flow Diagram of Wavelet Decomposition coupled with ANFIS Model)

In the first step, we just decompose the original signal into its wavelet approximation and detailed coefficients by using MATLAB's wavelet toolbox. For the above procedure we use discrete wavelet transform as it is much effective. We then obtain its coarser and finer parts via MATLAB. The trends are evinced by coarser scales and seasonal influences & noises are displayed by finer scales. From the different wavelets like Haar, Daubechies, Symlet, Morlet, etc. we choose Daubechies wavelet as it is best fit for our procedure. So, we use Daubechies of level 3 of different order [11]. So, we have

$$f(t) = D1 + D2 + D3 + A3$$

Then at the later stage we choose 6500 observations in total of Tata Power from which 5000 observations are for training purposes and 1500 are for testing purposes and similarly we choose 3300 observations in

total of Adani Power from which 2540 observations for training purposes and 760 for testing purposes. We make this combination in both the cases as 77% of total observation for training purpose and remaining 23% for testing purposes. Following figures (Fig 3a,3b,3c,3d) are showing training and testing graphs of Tata and Adani power time series data.

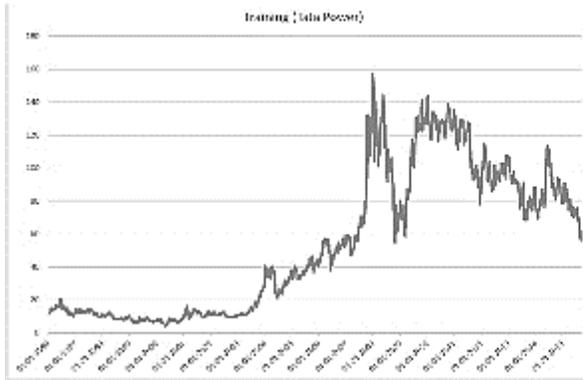


Fig. 3(a)- Training graph of Tata Power Closed Prices

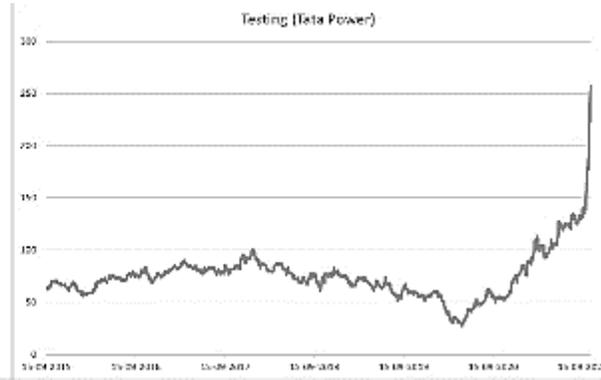


Fig. 3(b)- Testing graph of Tata Power Closed Prices



Fig. 3(c)- Training graph of Adani Power Closed Prices

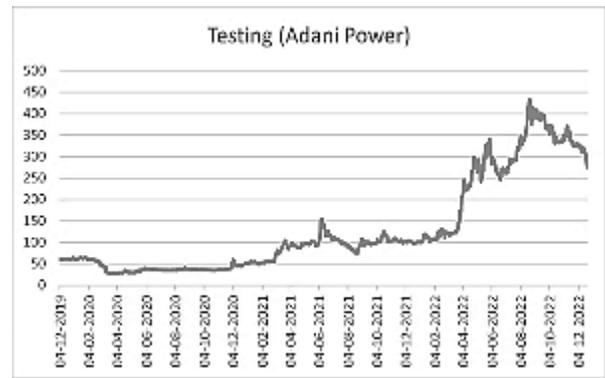


Fig.3(d)- Testing graph of Adani Power Closed Prices

For the comparison of the proposed methods, we consider three standard error measures and we called them as *KPIs (Key Performing Indicators)* and these are *Root Mean Square Error (RMSE)*, *Mean Absolute Error(MAE)* and *MSE (Mean Squared Error)*. These KPI measures are defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - f_i)^2}{n}}$$

$$MAE = \frac{\sum_{i=1}^n |y_i - f_i|}{n}$$

$$MSE = \frac{\sum_{i=1}^n (y_i - f_i)^2}{n}$$

Where  $y_i$ 's are the actual values,  $f_i$ 's are the forecasted values and  $n$  is the total number of observations.

Then at the last step, we applied ANFIS model on original data before applying wavelets on it and find their *RMSE*, *MAE* and *MSE*, our main *KPIs (Key Performing Indicators)* and then after that we apply wavelets on original data and simultaneously apply ANFIS model on signals one by one i.e., first to approximation coefficient  $a_3$ , then to detail coefficient  $D1$  and then similarly to other two detail coefficients  $D2$  &  $D3$ .

The statistical analysis of Tata Power & Adani Power daily stock market closed prices using ANFIS model without wavelets by [Table 1.1](#) & [Table 1.2](#) and with wavelets by [Table 2.1](#) & [Table 2.2](#).

Table 1.1: Analysis of Tata Power Daily Closed Prices Using ANFIS without Wavelets.

Original Data	Training Data			Testing Data		
	RMSE	MAE	MSE	RMSE	MAE	MSE
	4.2263	1.2215	17.8616	2.6414	1.3746	6.9769

Table 1.1

Table 1.2: Analysis of Adani Power Daily Closed Prices Using ANFIS without Wavelets

Original Data	Training Data			Testing Data		
	RMSE	MAE	MSE	RMSE	MAE	MSE
	3.777	1.2859	14.2657	7.8682	4.2827	61.9085

Table 1.2

Here we did not apply wavelets, we just used ANFIS model for our forecasting purposes and noted down some standard errors in both cases i.e., Tata Power and Adani Power.

Table 2.1: Analysis of Tata Power Daily Closed Prices using ANFIS with Wavelets.

Wavelet	Training Data			Wavelet	Testing Data		
	RMSE	MAE	MSE		RMSE	MAE	MSE
<b>Db2_L3</b>	3.6505	3.053	13.3261	Db2_L3	8.8979	3.9874	79.1726
<b>Db4_L3</b>	2.9324	1.243	8.5989	Db4_L3	3.7652	1.5155	14.1767
<b>Db6_L3</b>	2.5699	1.1346	6.6043	Db6_L3	2.6877	1.3150	7.2237
<b>Db8_L3</b>	<b>2.5216</b>	<b>1.0936</b>	<b>6.3584</b>	<b>Db8_L3</b>	<b>2.4856</b>	<b>1.2597</b>	<b>6.1782</b>
<b>Db10_L3</b>	2.3129	1.0253	5.3495	Db10_L3	2.6464	1.1940	7.0034

Table 2.1

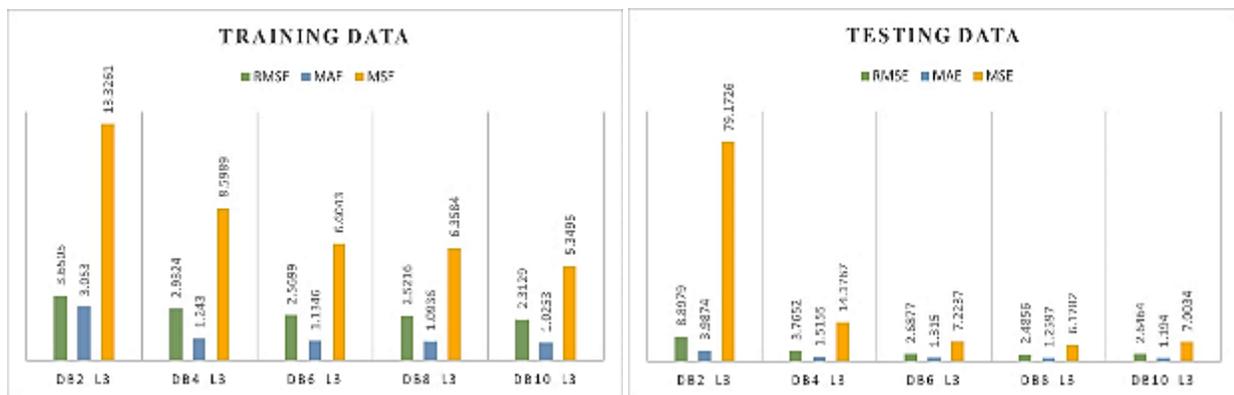


Fig. 4(a)-Errors from Training Data

Fig. 4(b)-Errors from Testing Data

Fig.4(a) & 4(b) showing difference between the errors of different models (Tata Power)

According to above data in [Table 2.1](#) and [figures 4\(a\) & 4\(b\)](#) of training and testing data of Tata Power daily closed prices, it is clear that **Db8\_Level-3** wavelet decomposition performs better among the other wavelets of different order in both the cases based on our KPIs.

Table 2.2: Analysis of Adani Power Stock Daily Closed Prices using ANFIS with Wavelets.

Training Data				Testing Data			
Wavelet	RMSE	MAE	MSE	Wavelet	RMSE	MAE	MSE
Db2_L3	3.3052	1.6757	10.9243	Db2_L3	12.448	5.8791	154.9527
Db4_L3	2.6219	1.3553	6.8743	Db4_L3	10.0019	4.8497	100.0380
Db6_L3	2.4169	1.2086	5.8414	Db6_L3	9.4915	4.5975	90.0885
<b>Db8_L3</b>	<b>2.1451</b>	<b>1.0937</b>	<b>4.6014</b>	<b>Db8_L3</b>	<b>7.3693</b>	<b>4.2663</b>	<b>54.3065</b>
Db10_L3	2.0935	1.091	4.3827	Db10_L3	8.6436	4.360	74.7118

Table 2.2

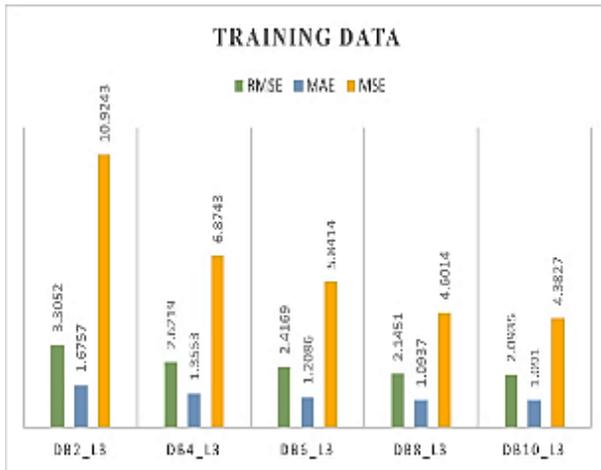


Fig. 5(a)- Errors from Training Data

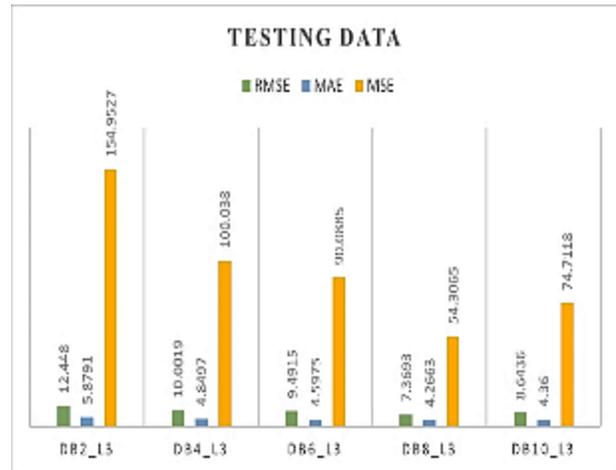


Fig. 5(b)- Errors from Testing Data

*Fig.5(a) & 5(b) showing difference between the errors of different models(Adani Power)*

Similarly, in above data in [Table 2.2](#) and [figures 5\(a\) & 5\(b\)](#) of training and testing data of Adani Power Daily Closed Prices, here it is also clear that Db8\_Level-3 wavelet decomposition performs better among the other wavelets of different order in both the cases based on our KPIs.

The [Tables 2.1](#) and [2.2](#) make it quite evident that we must stop using Db10 because in testing phase KPIs are deterred from those of Db8. Therefore, we see that as we used ANFIS model, on both the data i.e., Tata Power & Adani Power daily closed prices, after applying wavelets with the mother wavelet Daubechies of different orders with level-3 we get the results better from the ANFIS on data without wavelet decomposition.

The original data from Tata Power is tested and forecasted in the graphs below in [fig. 6](#) (using solely ANFIS), and [fig. 6\(a\)](#) is a zoomed-in version of [fig. 6](#) that displays values from 1335 to 1375. Clearly, there is no overlapping of blue (forecasted) and red (tested) lines.

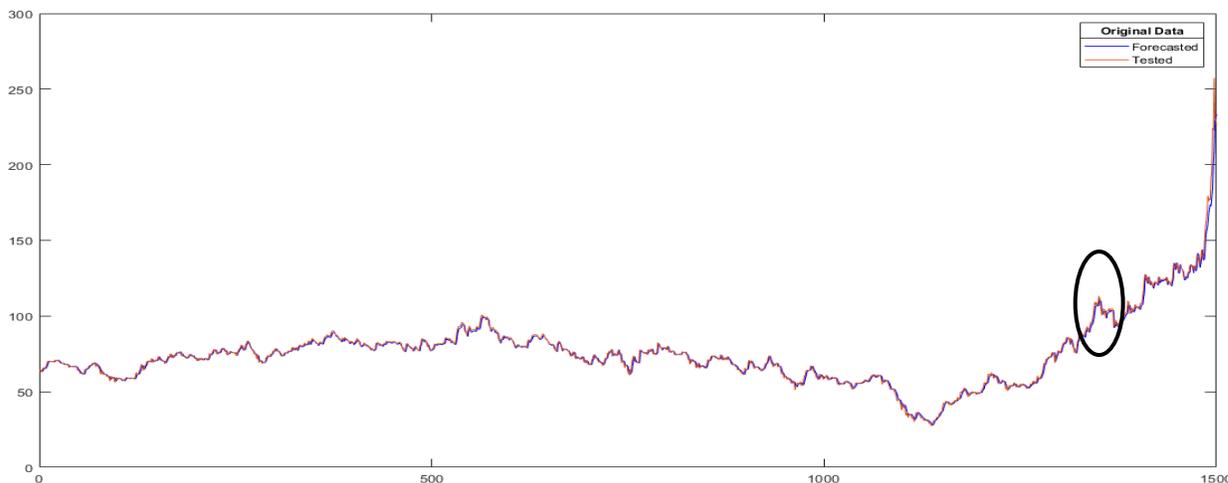


Fig. 6: Time Series Plot for Tata Power Original Data of all 1500 tested and forecasted values.

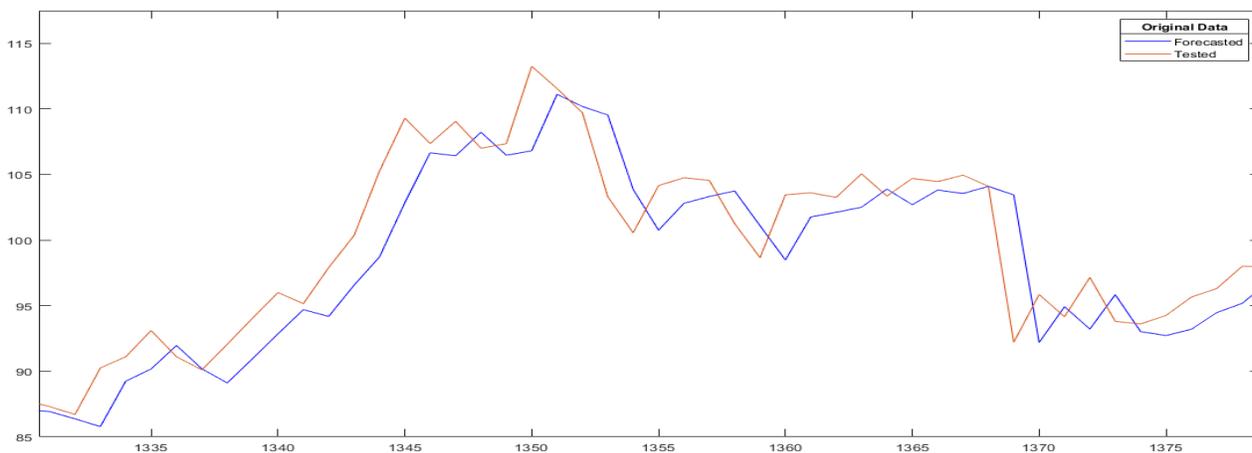


Fig. 6(a): Time Series Plot for Tata Power Original Data (Zoomed Version of 40 Values)

Yet, the ANFIS-Wavelet graphs in the [figure 7\(a\)](#) indicate values from 1335 to 1375 for the Daubechies of Order 8 level-3 (Db8 Level-3) and the total 1500 values for the ANFIS-Wavelet graph in [figure 7](#). In the majority of the values, it is evident that the black (forecasted) and red (tested) lines overlap.

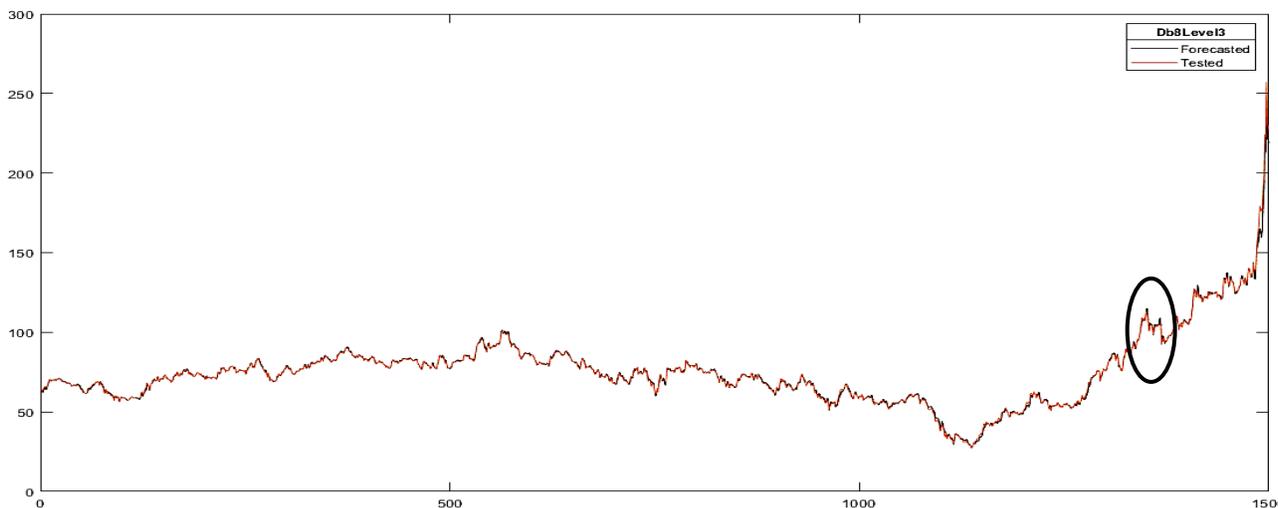


Fig. 7: Time Series Plot for Tata Power Db8\_Level-3 of all 1500 Values

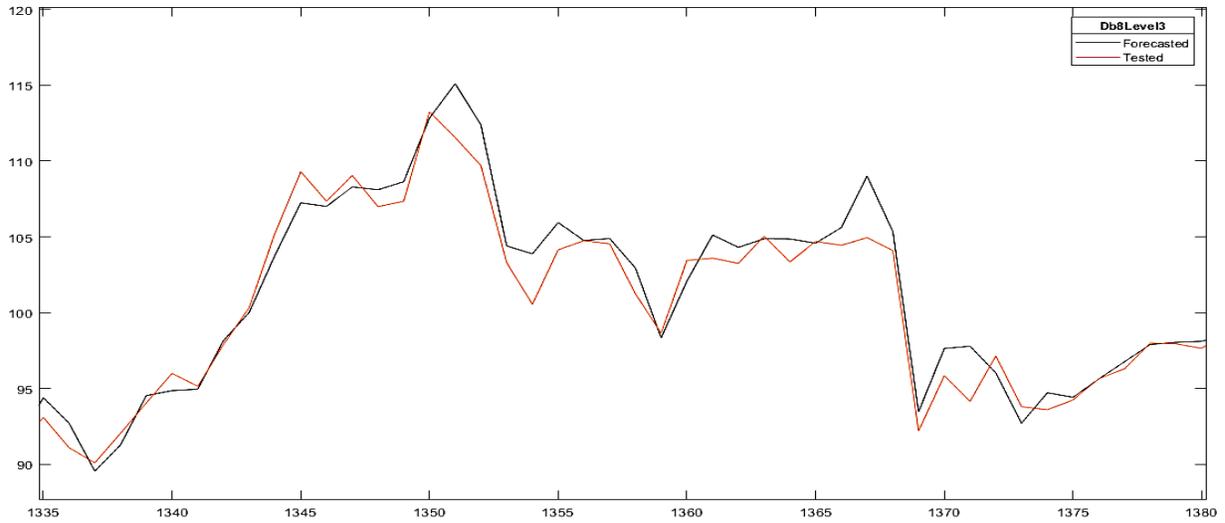


Fig. 7(a): Time Series Plot for Tata Power Db8\_Level-3 of 40 Values

Also, [fig 8\(a\)](#), [8\(b\)](#), [8\(c\)](#) & [8\(d\)](#) are showing the testing error, training data of A3, D1, D2 & D3, testing data of A3, D1, D2 & D3 and trained data with predicted output of Tata Power stock daily closed prices.

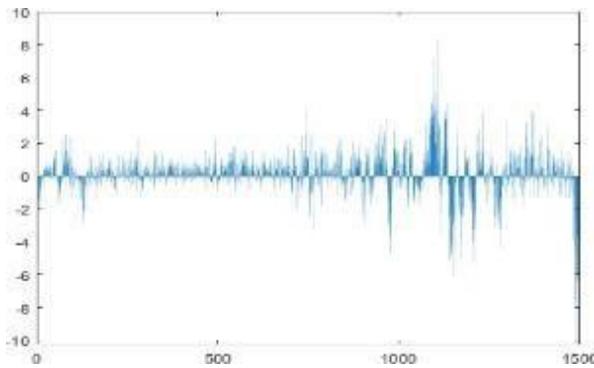


Fig. 8(a)-Testing Error of Tata Power closed prices

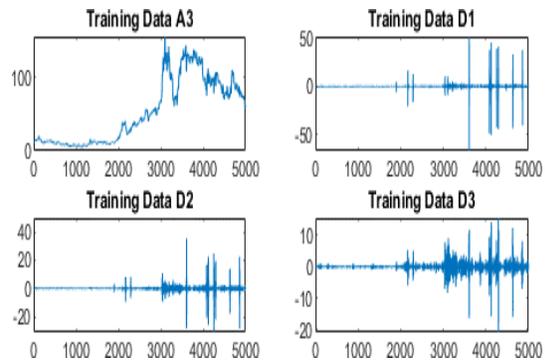


Fig. 8(b)- Training data of A3, D1, D2 & D3 Signals

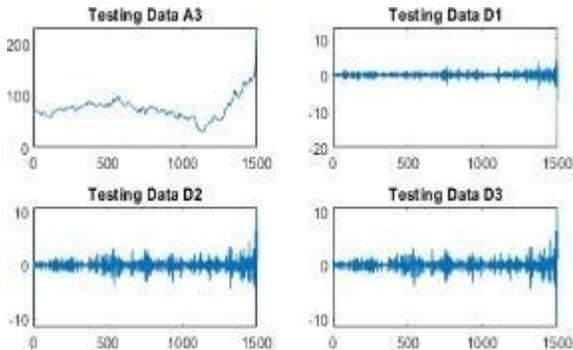


Fig. 8(c)- Testing data of A3, D1, D2 & D3 Signals

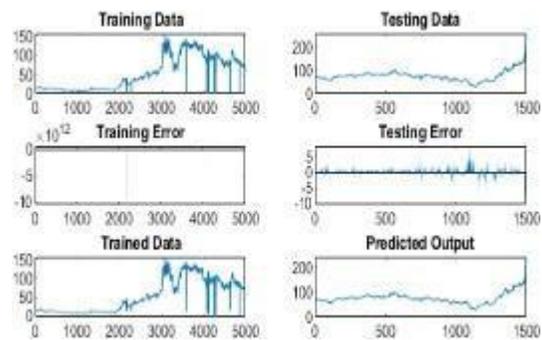


Fig. 8(d)- Trained data with predicted output of Tata Power closed prices

The original data from Adani Power is tested and forecasted in the graphs below in [fig. 9](#) (using solely ANFIS), and [fig. 9\(a\)](#) is a zoomed-in version of [fig. 9](#) that displays values from 440 to 500. Clearly, there is no overlapping of blue (forecasted) and red (tested) lines.

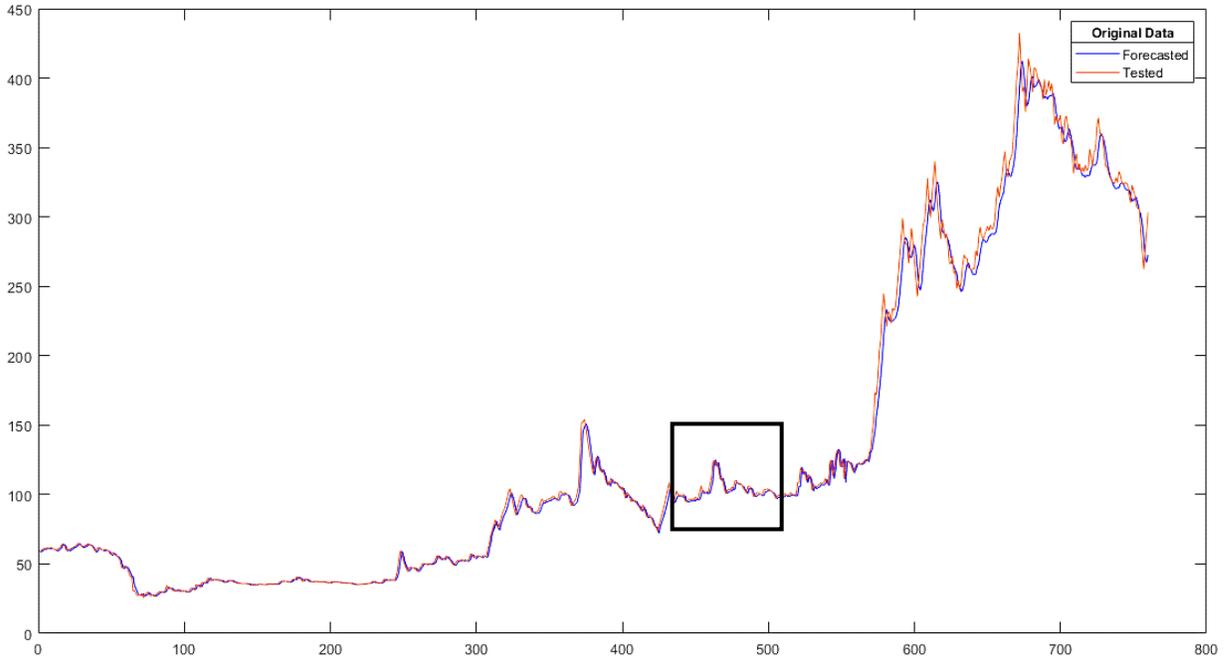


Fig. 9: Time Series Plot for Adani Power Original Data of overall 760 observations

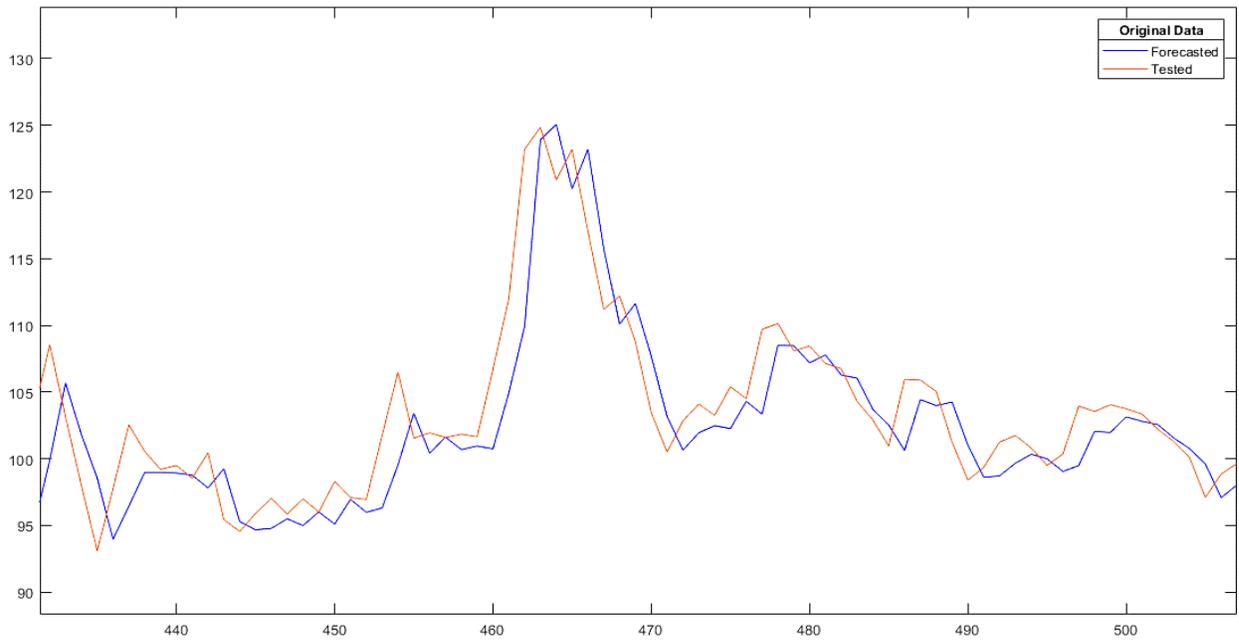


Fig. 9(a): Time Series Plot for Adani Power Original Data (Zoomed Version of 60 Values)

But here [fig.10](#) and [fig. 10\(a\)](#) shows the ANFIS-Wavelet graphs showing the overall 760 values and zoomed version of [fig.10](#) of Daubechies of Order 8 level-3 (Db8\_Level-3), showing the values from 440 to 500. Clearly, there is overlapping of black (forecasted) and red (tested) lines in most of the values.

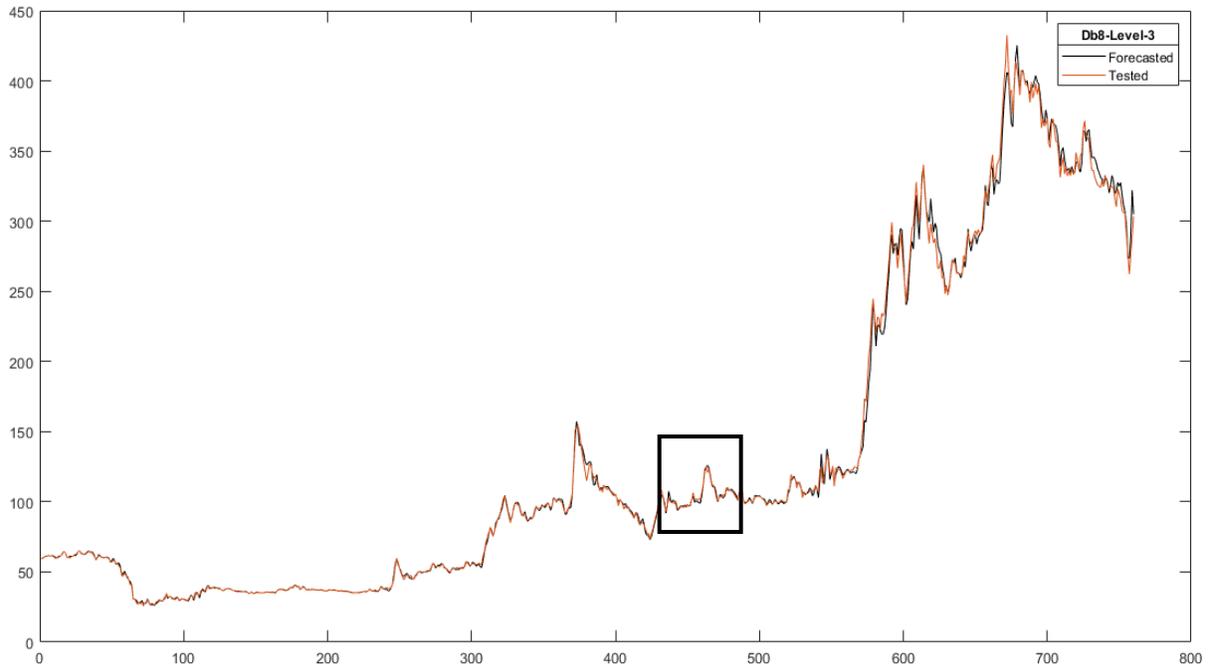


Fig. 10: Time Series Plot for Adani Power Db8\_Level-3 of overall 760 observations

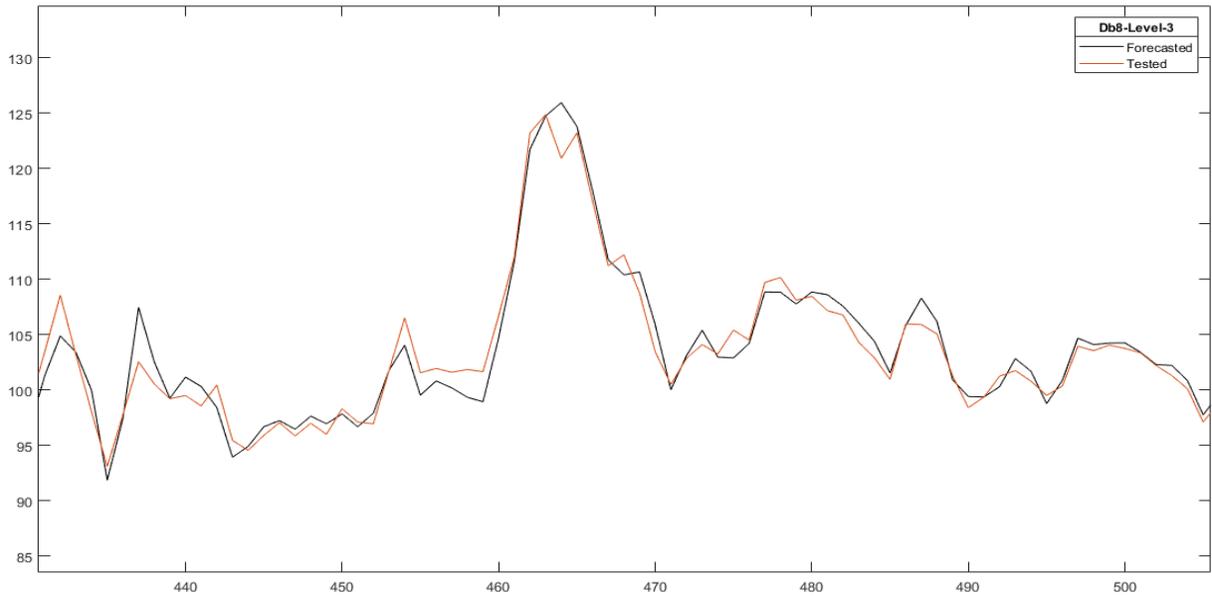


Fig.10(a): Time Series Plot for Adani Power Db8\_Level-3 data of 60 Values (Zoomed Version)

Also, fig 11(a),11(b),11(c) and 11(d) are showing the testing error, training data of A3, D1, D2 & D3, testing data of A3, D1, D2 & D3 and trained data with predicted output of Adani Power stock daily closed prices.

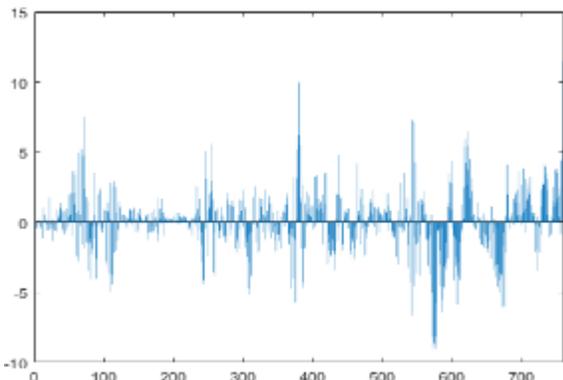


Fig. 11(a)- Testing Error of Adani Power closed prices

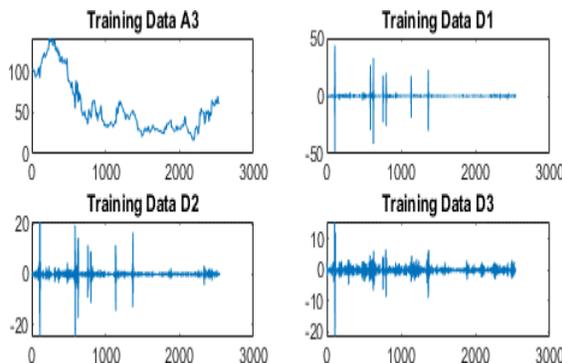


Fig. 11(b)- Training data of A3, D1, D2 & D3 Signals

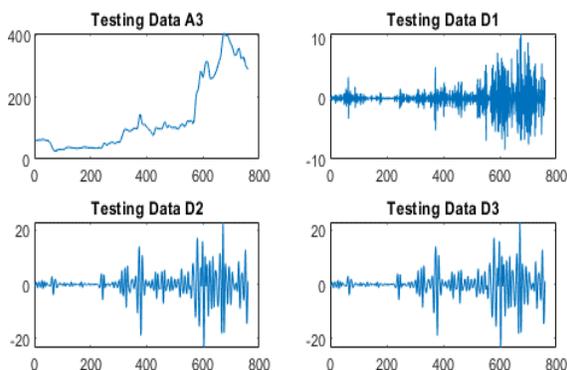


Fig. 11(c)- Testing data of A3, D1, D2 & D3 Signals

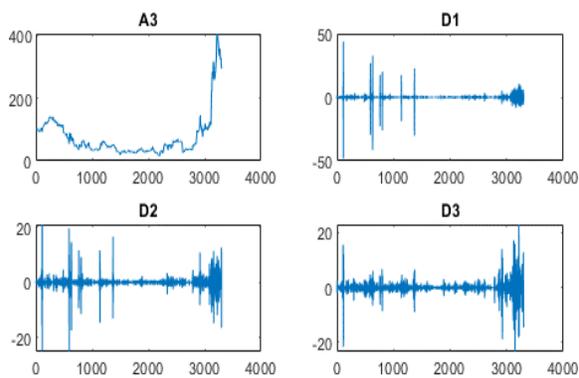


Fig. 11(d)- Trained data with predicted output of Adani Power closed prices

### 3. Results

Table 3.1: Results showing the values of KPIs with and without wavelets for Tata Power.

KPIs	Training			Testing		
	RMSE	MAE	MSE	RMSE	MAE	MSE
Without Wavelet	4.2263	1.2215	17.8616	2.6414	1.3746	6.9765
With Wavelet	2.5216	1.0936	6.3584	2.4856	1.2597	6.1782
%Age Difference	40.33%	10.47%	64.40%	5.89%	8.35%	11.44%

Table 3.1

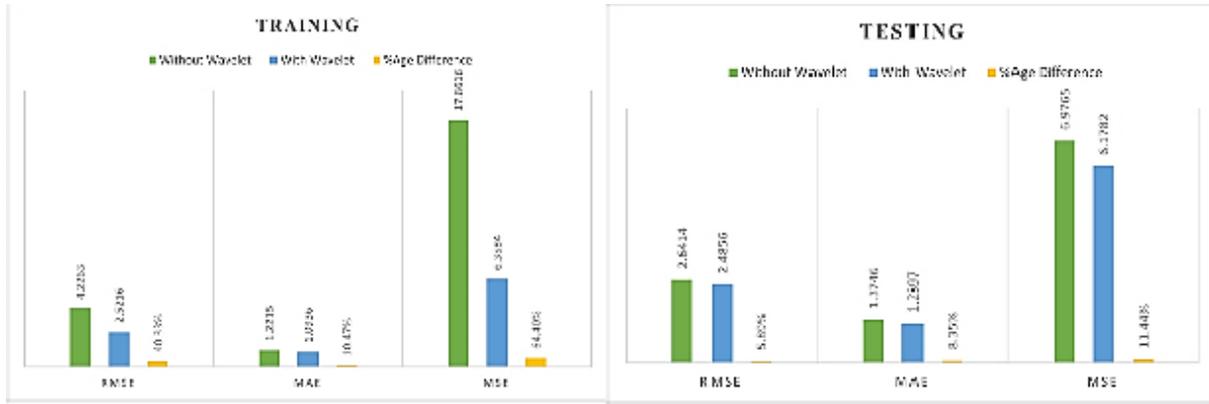


Fig. 12(a)-Training Errors with and Without Wavelet

Fig. 12(b)- Testing Errors with and Without Wavelet

Fig 12(a) & Fig 12 (b) Showing comparison of KPIs (ANFIS With and Without Wavelet for Tata Power Closed Prices)

Here, in the case of Tata Power, from the given data in Table 3.1 and figures 12(a) & 12(b) of training and testing, we can easily see that ANFIS combined with Wavelet perform much better than ANFIS alone i.e., without wavelet.

Table 3.2: Results showing the values of KPIs with and without wavelets for Adani Power.

KPIs	Training			Testing		
	RMSE	MAE	MSE	RMSE	MAE	MSE
<b>Without Wavelet</b>	3.777	1.2859	14.2657	7.8682	4.2827	61.9085
<b>With Wavelet</b>	2.1451	1.0937	4.6014	7.3693	4.2663	54.3065
<b>%Age Difference</b>	43.20%	14.94%	67.74%	6.34%	0.38%	12.27%

Table 3.2

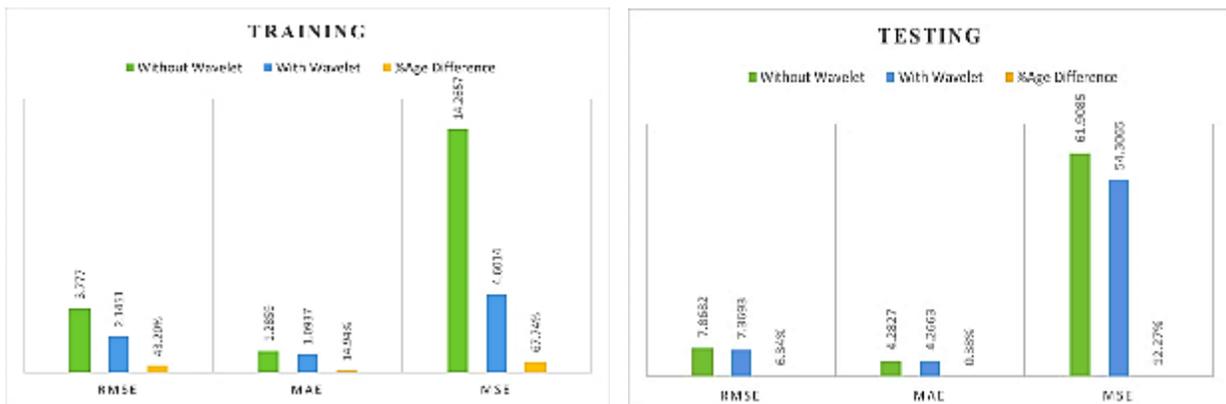


Fig. 13(a)-Training Errors with and Without Wavelet

Fig. 13(b)-Testing Errors with and Without Wavelet

Fig 13(a) & Fig 13(b) Showing comparison of KPIs (ANFIS With and Without Wavelet for Adani Power Closed Prices)

Similarly in the case of Adani Power, from the given data in [Table 3.2](#) and [figures 13\(a\) & 13\(b\)](#) of training and testing, we can easily see that ANFIS combined with Wavelet perform much better than ANFIS alone i.e., without wavelet.

#### 4. Conclusion

This study demonstrates the effectiveness of integrating wavelet transforms with the Adaptive Neuro-Fuzzy Inference System (ANFIS) for stock price forecasting. By using the Daubechies (Db8) wavelet at level 3, the hybrid ANFIS-Wavelet model significantly outperformed the standard ANFIS in both training and test phases. For Tata Power, RMSE improved by 40.33% in training and 5.89% in testing, MAE decreased by 10.47% in training and 8.35% in testing, and MSE dropped by 64.40% in training and 11.44% in testing. Similarly, for Adani Power, RMSE improved by 43.20% in training and 6.34% in testing, MAE by 14.94% in training and 0.38% in testing, and MSE by 67.74% in training and 12.27% in testing. These improvements highlight the superiority of the ANFIS-Wavelet model in capturing complex, non-stationary patterns, offering enhanced accuracy for stock price predictions. This hybrid approach provides a valuable tool for financial analysts and can be applied broadly to other time series forecasting challenges.

#### 5. Acknowledgements

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#### 6. Conflict of Interest

No conflict.

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