Short Term Course on

Introduction to Data Science using Python (IDSP-2024)

Hybrid Mode (Online & Offline)

20th-24th May 2024

Department of Computer Science & Engineering

National Institute of Technology Rourkela – 769008

Conveners

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Time Series Forecasting using Machine Learning and Hybrid Models

By

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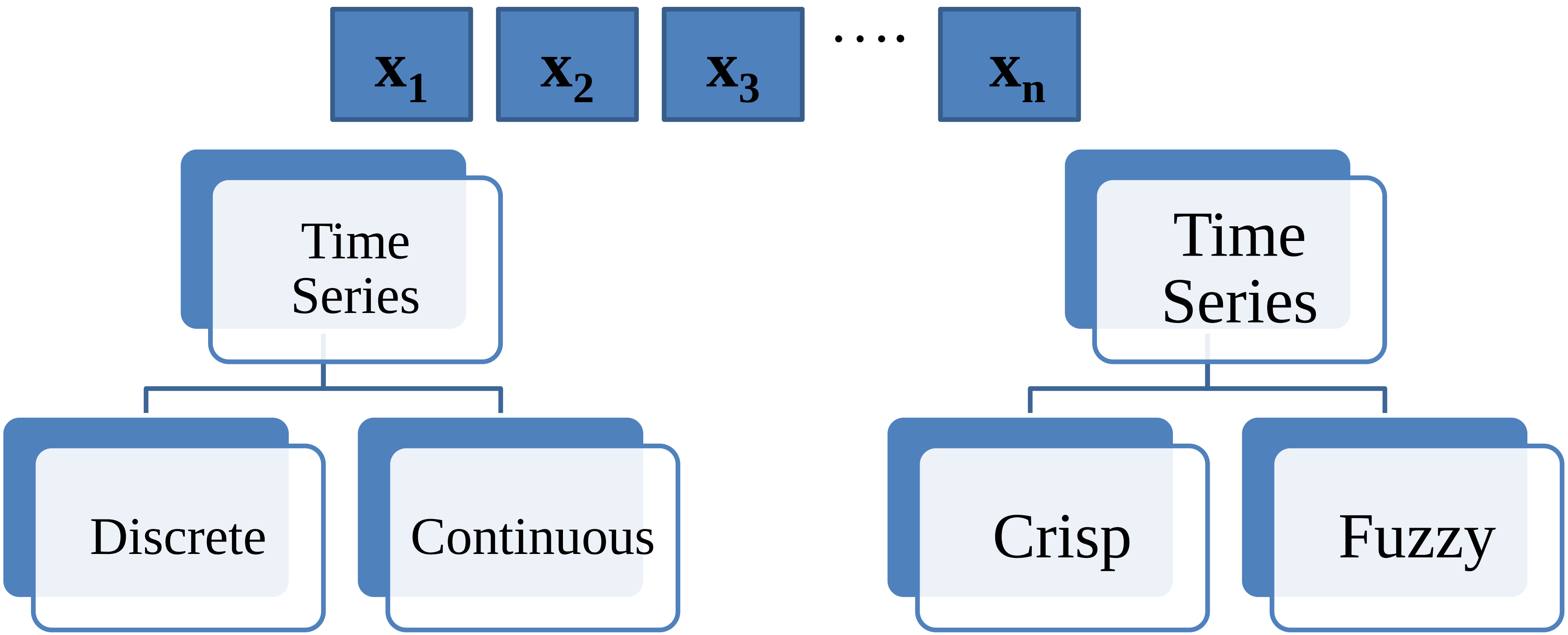
OUTLINES…

- Introduction and Motivation
- **Time Series Forecasting using Machine Learning Models**
- **Hybrid Time Series Forecasting using Machine Learning Models**
  - Additive Hybrid Models
  - Multiplicative Hybrid Models
  - Parallel Hybrid Models
  - Decomposition Based Hybrid Models
- **Fuzzy Time Series Forecasting**
  - Ignoring Membership Values
  - Considering Membership Values (Traditional, Intuitionistic, Hesitant & Neutrosophic Fuzzy Set)

INTRODUCTION

- Time Series
  - A time series is a set of observations of the same variable measured sequentially through time.

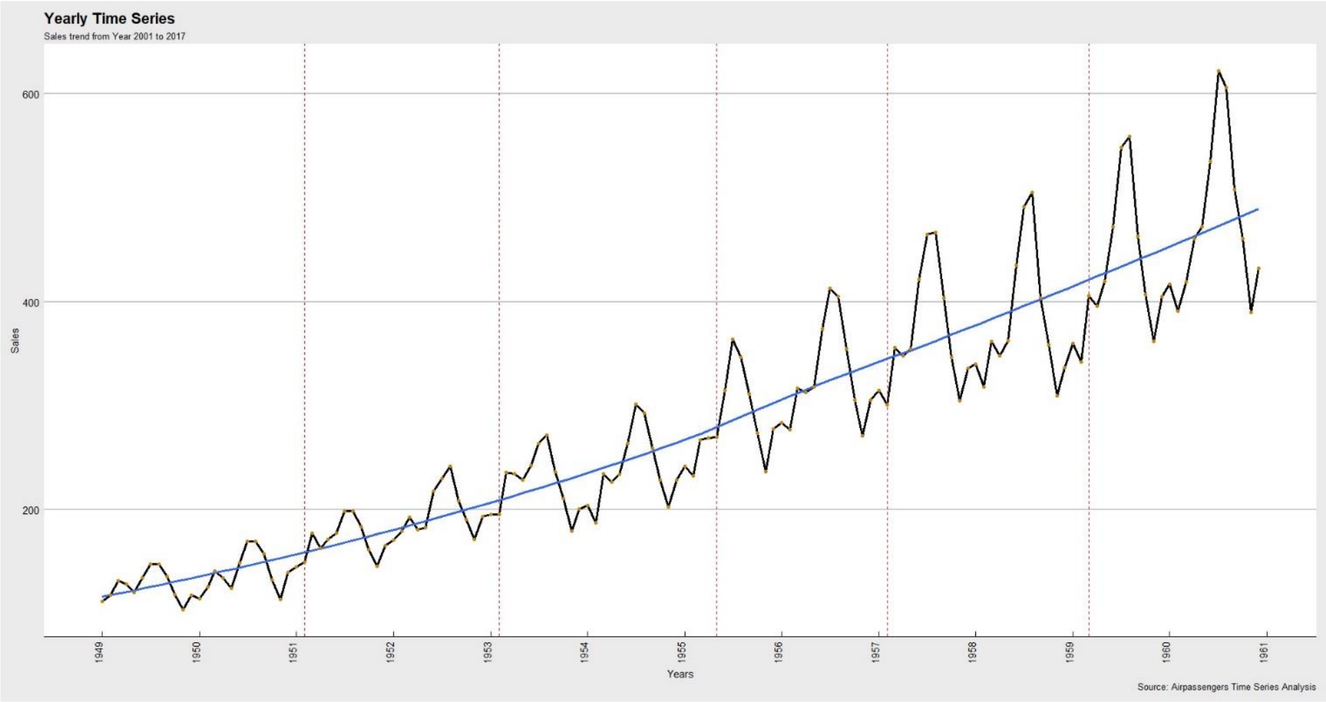


INTRODUCTION

- **Components of Time Series**
  - Trend
  - Seasonal
  - Cyclical
  - Irregular

INTRODUCTION

- **Components of Time Series**
  - **Trend:** Trend is a pattern in data that shows the movement of a series to relatively **higher or lower values over a long period of time**.
  - Seasonal
  - Cyclical
  - Irregular



 Decreasing Trend

INTRODUCTION

- **Components of Time Series**
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  - Cyclical
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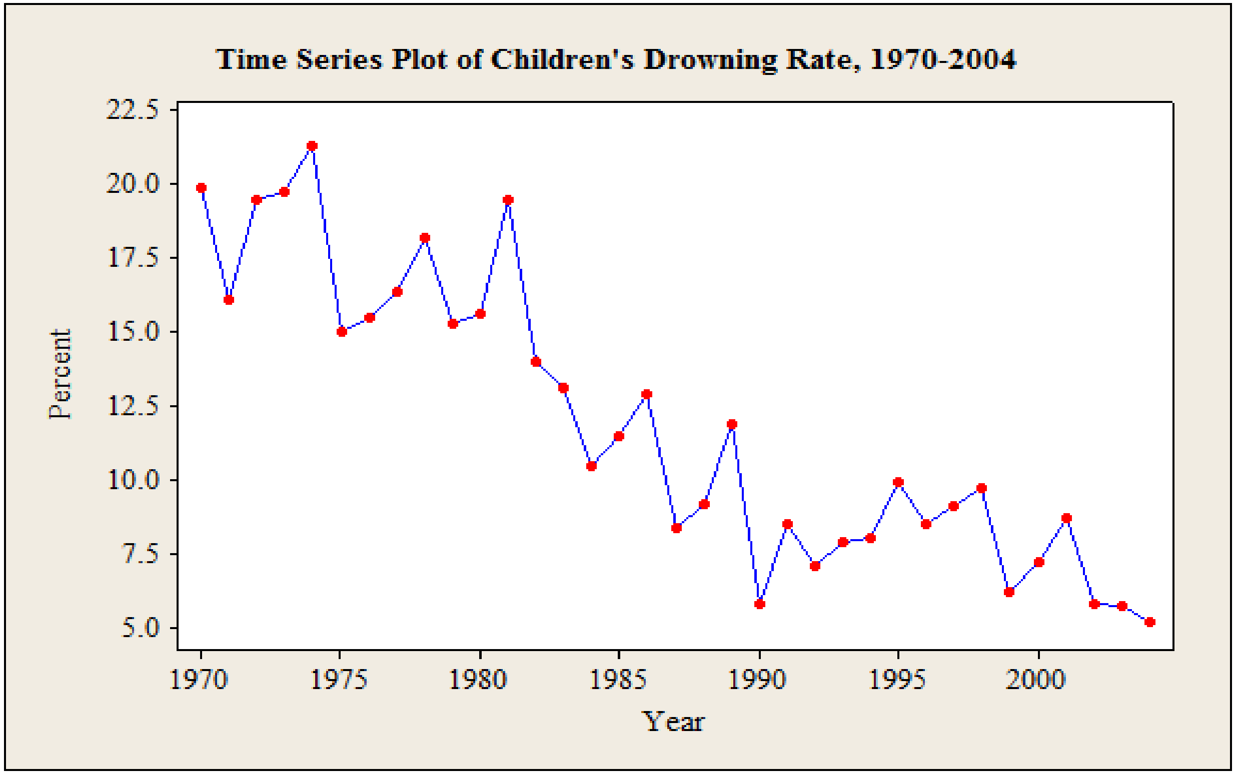


INTRODUCTION

- **Components of Time Series**
  - **Trend:** Trend is a pattern in data that shows the movement of a series to relatively higher or lower values over a long period of time.
    - **Trend component can be treated using differencing (desired order).**
    - e.g. Time Series: 8, 13, 18, 14, 13, 18,..
    - 1st Differenced Time Series: 5, 5, -4, -1, 5
    - Reverse De-Trending : 8

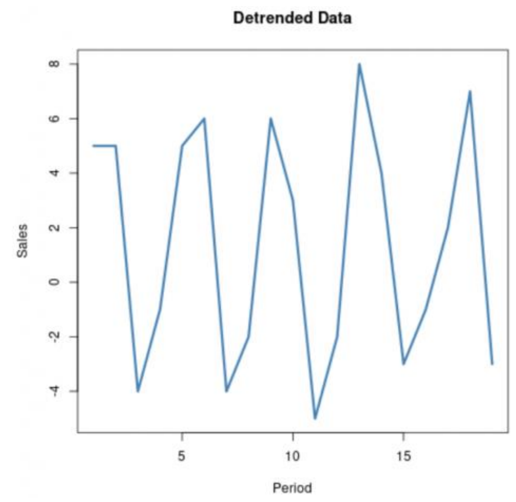
      8+5= 13

      13+5=18

      18+-4 =14

      14+-1 =13

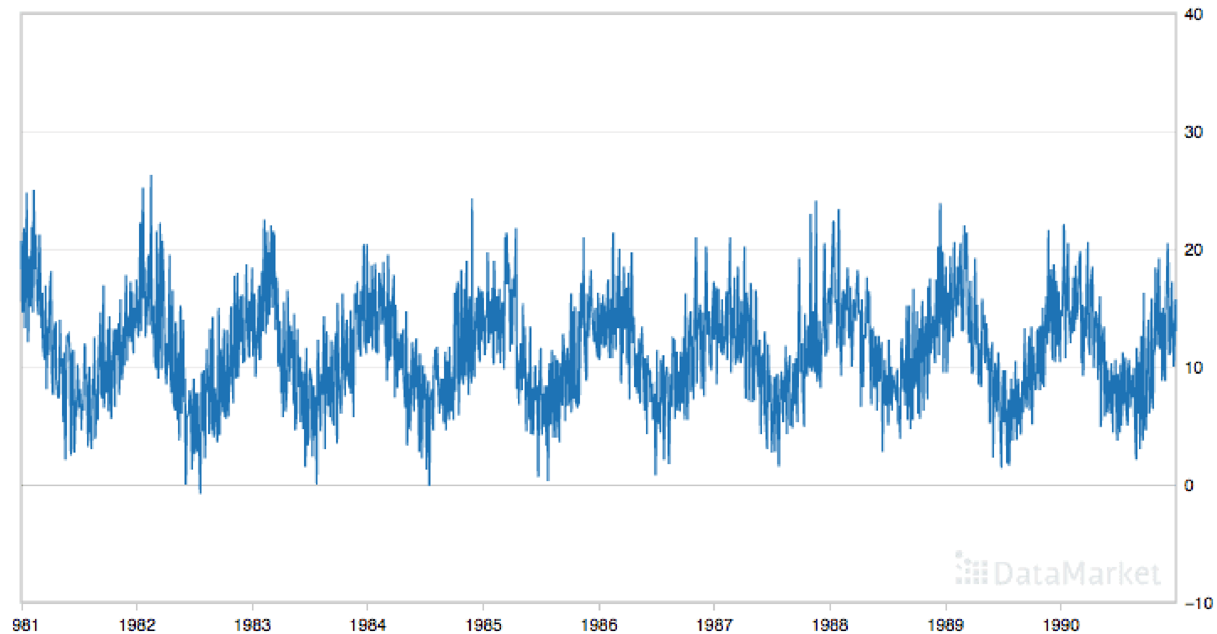
      13+5 =18



  - Python Code Link: https://machinelearningmastery.com/remove-trends-seasonality-difference-transform-python/

INTRODUCTION

- **Components of Time Series**
  - Trend
  - **Seasonal:** Seasonality, as its name suggested, refers to the seasonal characteristics of the time series data. It is the predictable pattern that repeats at a certain frequency within one year, such as weekly, monthly, quarterly, etc.
  - Cyclical
  - Irregular



INTRODUCTION

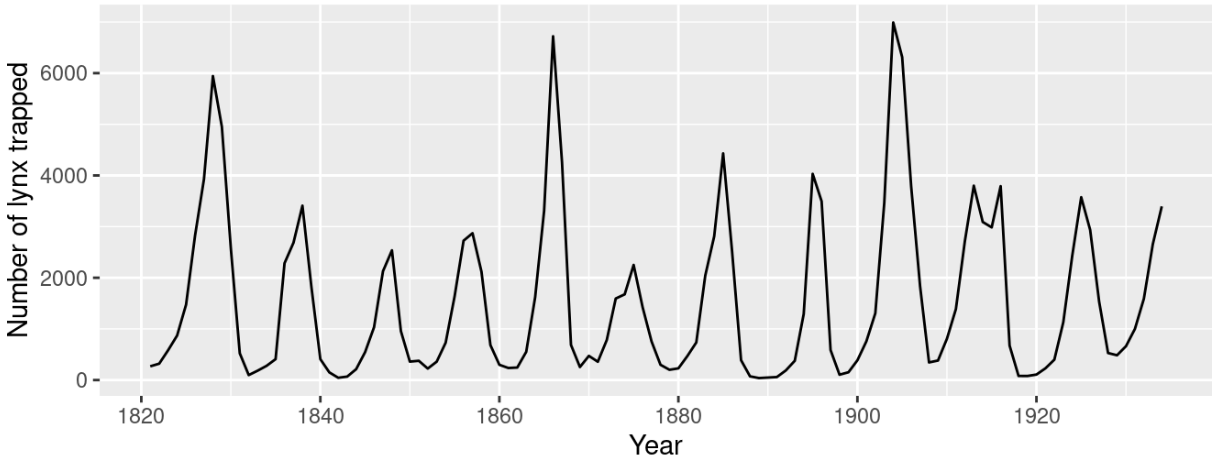
- **Components of Time Series**
  - Trend
  - **Seasonal:** Seasonality, as its name suggested, refers to the seasonal characteristics of the time series data. It is the predictable pattern that repeats at a certain frequency within one year, such as weekly, monthly, quarterly, etc.
    - **Seasonal component can be treated using seasonal differencing.**
      - We can remove seasonality in the data using differencing, which calculates the difference between the current value and its value in the previous season.
    - e.g. Time Series: 1,3,-5,0,4,-4
    - Seasonal Differenced Time Series: -1,1,1, …
      (Seasonal Length-3)
    - Reverse process : 1+-1= 0
      3+1= 4
      -5+1= -4
  - Python Code Link: https://machinelearningmastery.com/remove-trends-seasonality-difference-transform-python/

INTRODUCTION

- **Components of Time Series**
  - Trend
  - **Seasonal:** Seasonality, as its name suggested, refers to the seasonal characteristics of the time series data. It is the predictable pattern that repeats at a certain frequency within one year, such as weekly, monthly, quarterly, etc.
    - **Seasonal component can be treated using seasonal differencing using seasonal average.**
      - We can remove seasonality in the data using differencing by seasonal average, which calculates the difference between the current value and its seasonal average.
    - e.g. Time Series: 1,3,-5,1, 3, -5…
    - Seasonal Average (Season Length:3): 1, 3, -5
    - Seasonal Differenced Time Series: 0, 0, 0, 0, 0, 0 …
      (Seasonal Length-3)
    - Reverse process : 0+-1= 1
      0+3= 3
      0+-5= -5

INTRODUCTION

- **Components of Time Series**
  - Trend
  - Seasonal
  - **Cyclical:** The cyclical component of a time series refers to (regular or periodic) fluctuations excluding the irregular component.
  - Irregular



INTRODUCTION

- **Components of Time Series**
  - Trend
  - Seasonal
  - Cyclical
  - **Irregular:** This component is unpredictable. Every time series has some unpredictable component that makes it a random variable.

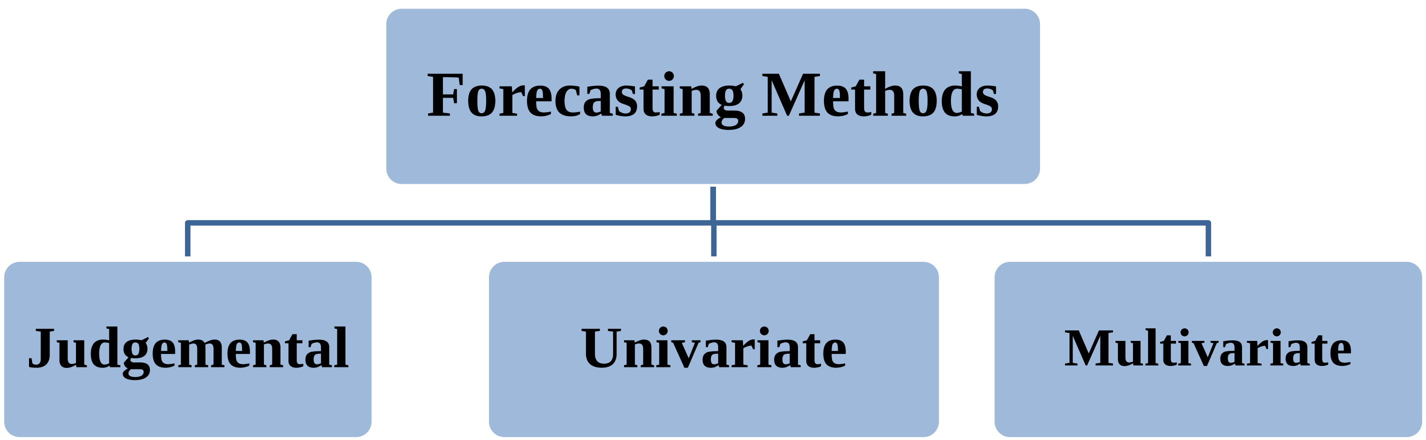
INTRODUCTION

- **Time Series Forecasting**
  - **Time series forecasting (TSF)** is the *process of predicting* the *future outcomes* of a phenomenon by ***systematically analyzing its past observations***.

x_1 x_2 x_3 …… x_n ? x_{n+h}

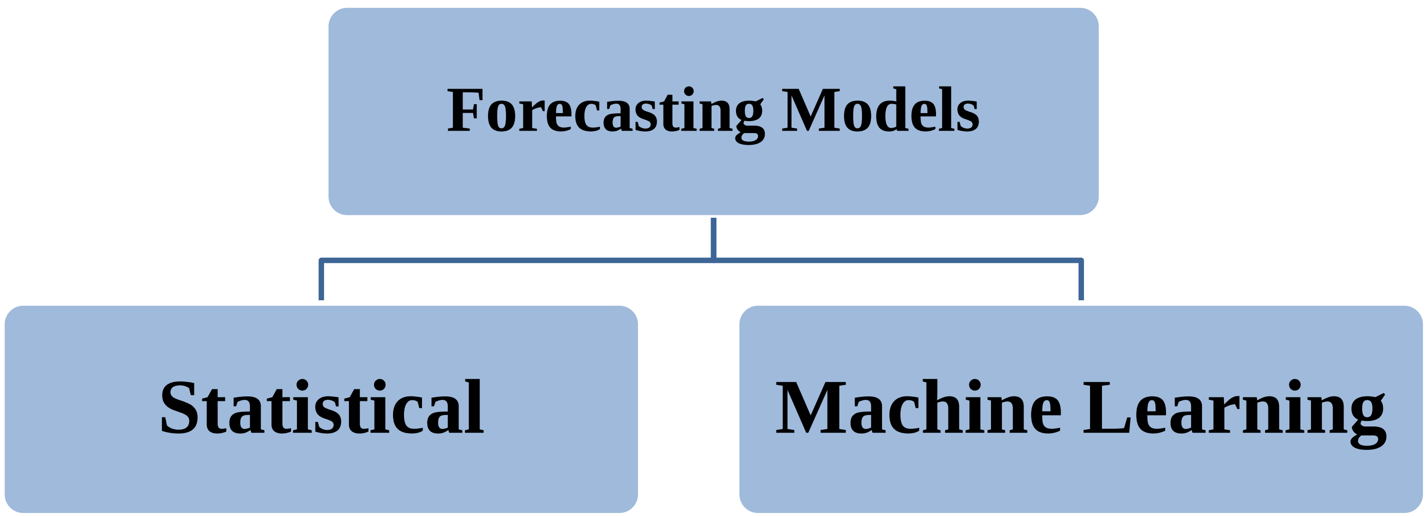
INTRODUCTION

- **Forecasting Method:**
  - A forecasting method is a procedure to predict the future values by systematically analyzing the past observations.



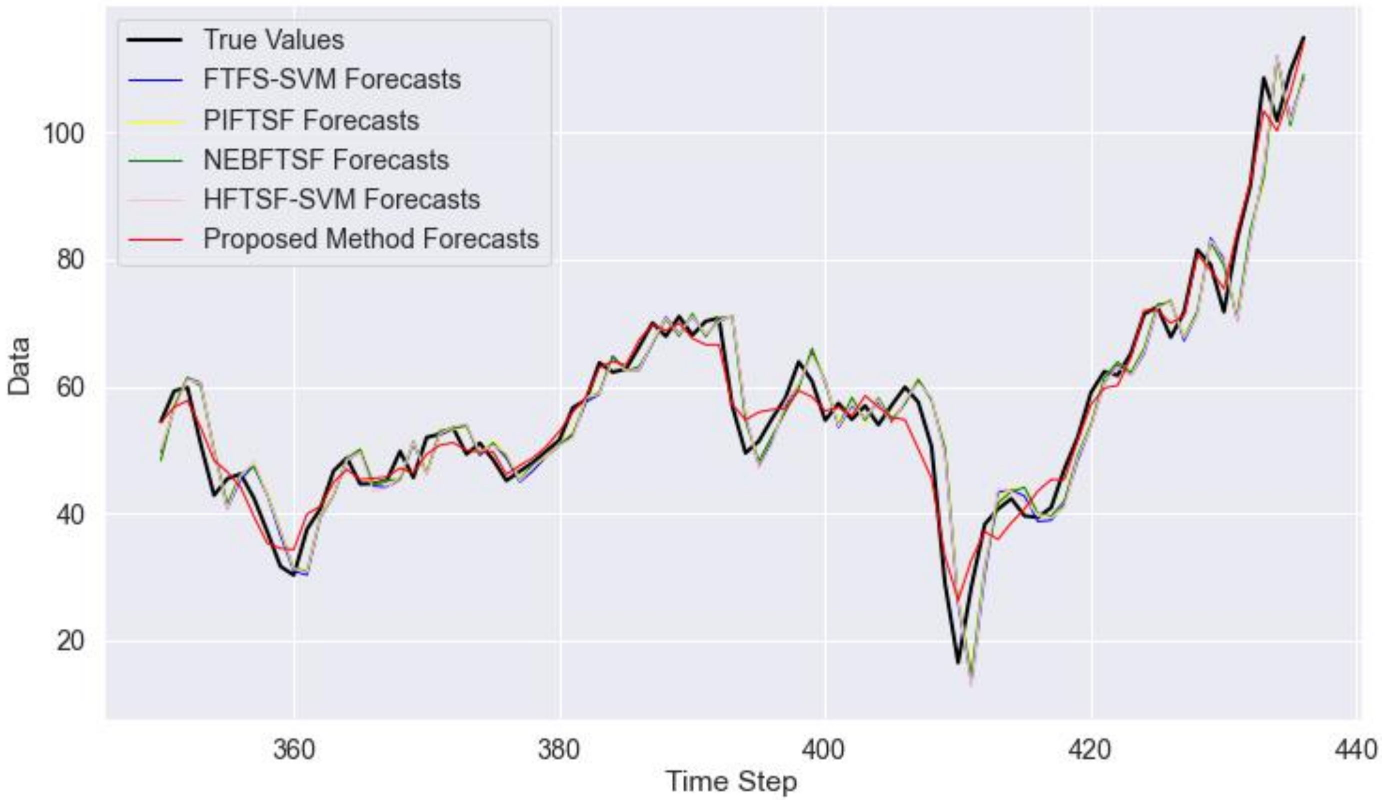
INTRODUCTION

- **Forecasting Model:**
  - A forecasting model is a tool to reveal the relationship existing in past data and using which the future values are predicted.



INTRODUCTION

- **Point vs Interval Forecasting**
  - **Point (Deterministic) Forecasting**



INTRODUCTION

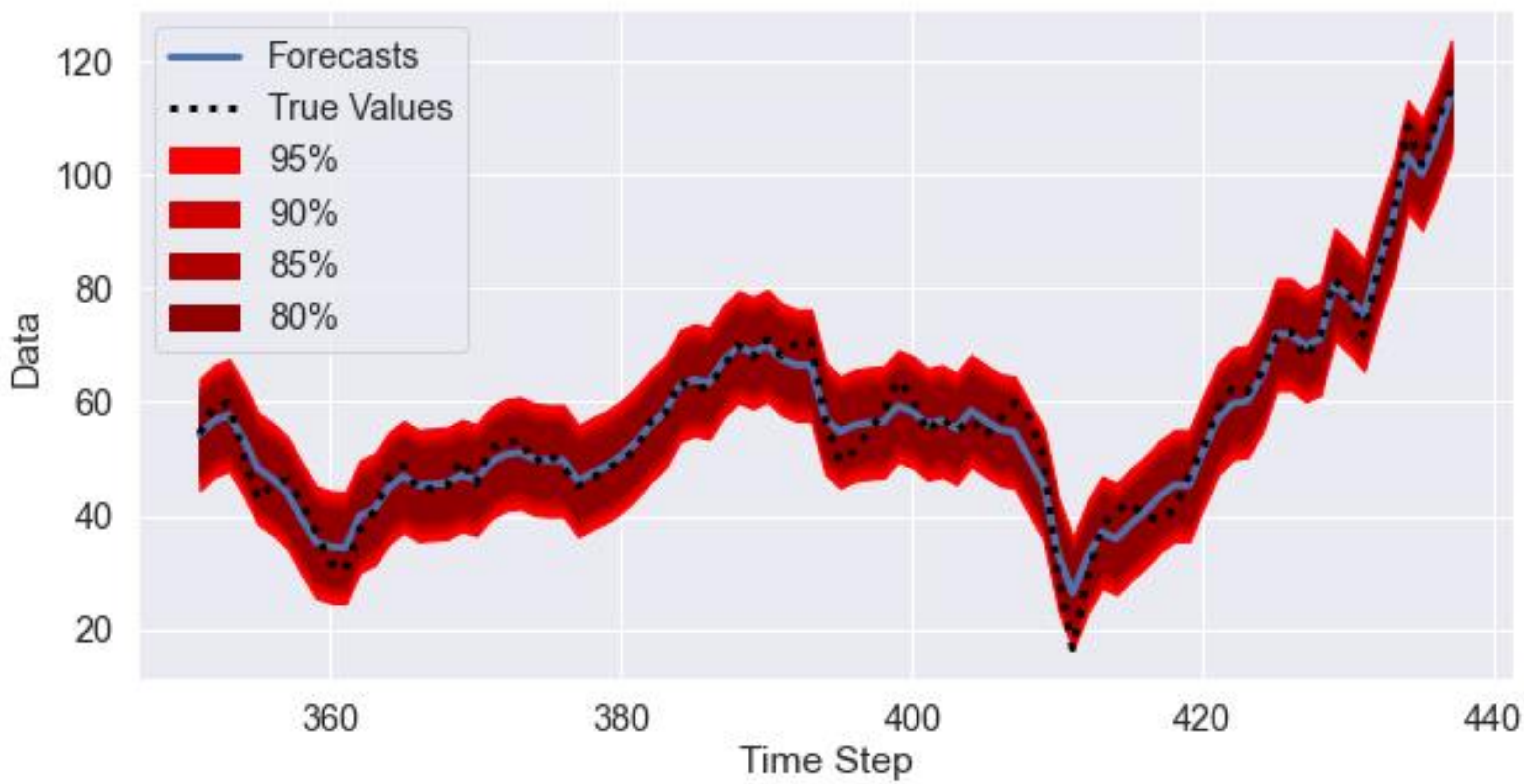
- **Point Forecasting Accuracy Measures**

Error-metric	Accuracy Measure	Formula
Scale-dependent	Mean Absolute Error (MAE) or Mean Absolute Deviation (MAD)	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert$
	Geometric Mean Absolute Error (GMAE)	$\left(\prod_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert\right)^{\frac{1}{n}}$
	Mean Square Error (MSE)	$\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$
	Root Mean Square Error (RMSE)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$
Percentage	Mean Absolute Percentage Error(MAPE)	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert y_i-\hat{y}_i\rvert}{y_i}\times 100$
	Symmetric Mean Absolute Percentage Error(SMAPE)	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert y_i-\hat{y}_i\rvert}{(\lvert y_i\rvert+\lvert\hat{y}_i\rvert)/2}$
Relative	Median Relative Absolute Error (MdRAE)	$median\left(\left\lvert\frac{y_i-\hat{y}_i}{y_i-\hat{y}_i^*}\right\rvert\right)$
	Geometric Mean Relative Absolute Error (GMRAE)	$\left(\prod_{i=1}^{n}\left\lvert\frac{y_i-\hat{y}_i}{y_i-\hat{y}_i^*}\right\rvert\right)^{\frac{1}{n}}$
Scale-free	Mean Absolute Scaled Error (MASE)	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert y_i-\hat{y}_i\rvert}{\frac{1}{n-1}\sum_{j=2}^{n}\lvert y_i-y_{i-1}\rvert}$

where y_i and $\hat{y}_i$ denote the ith actual and forecasted value, n denotes the number of observations. **Lower the value better the forecasts.**

INTRODUCTION

- **Point vs Interval Forecasting**
  - **Interval (Probabilistic) Forecasting:**



INTRODUCTION

- **Interval Forecasting Accuracy Measures**

$$Prediction\ Interval\ Coverage\ Probabilty\ (PICP^{(\alpha)}) = \frac{1}{n}\sum_{i=1}^{n} C_i\ ,\ C_i = \begin{cases} 1 & y_i \in [L_i^{(\alpha)}, U_i^{(\alpha)}] \\ 0 & y_i \notin [L_i^{(\alpha)}, U_i^{(\alpha)}] \end{cases}$$

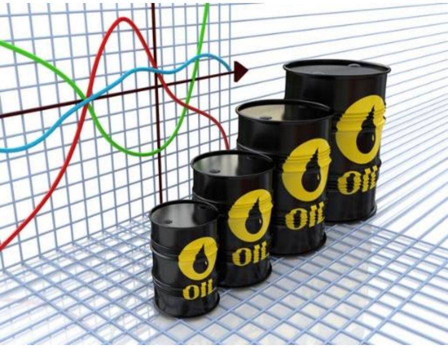
$$Prediction\ Interval\ Normalized\ Average\ Width\ (PINAW^{(\alpha)}) = \frac{1}{nR}\sum_{i=1}^{n}(U_i^{\alpha} - L_i^{\alpha})$$

$$Accumulated\ Width\ Deviation\ (AWD^{(\alpha)}) = \frac{1}{n}\sum_{i=1}^{n} AWD_i^{\alpha}\ ,AWD_i^{\alpha} = \begin{cases} \frac{L_i^{(\alpha)} - y_i}{U_i^{(\alpha)} - L_i^{(\alpha)}}, y_i < L_i^{(\alpha)} \\ 0 \quad ,\ y_i \in [L_i^{(\alpha)}, U_i^{(\alpha)}] \\ \frac{y_i - U_i^{(\alpha)}}{U_i^{(\alpha)} - L_i^{(\alpha)}}, y_i > U_i^{(\alpha)} \end{cases}$$

$$Average\ Coverage\ Error\ (ACE^{(\alpha)}) = PICP^{(\alpha)} - PINC^{(\alpha)}$$

α denotes the significance level, $L_i^{(\alpha)}$ and $U_i^{(\alpha)}$ denote the lower bound and upper bound for ith data point. **The lower values of PINAW, and AWD are desirable, while the higher values of PICP and ACE are desirable for a better model.**

MOTIVATION



Crude Oil

Stock Price

Retail Industry

Internet Traffic

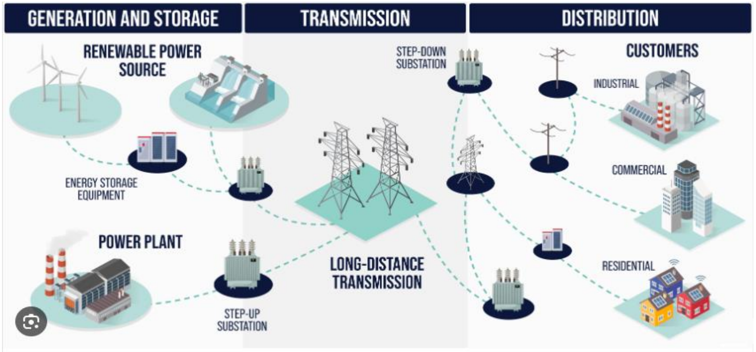
Electricity Price

Call Volume

Flood

Earthquake

MOTIVATION



Electricity Load Forecasting

Air Quality Index Forecasting

Rainfall Forecasting

Streamflow Forecasting

Agricultural Product Price Forecasting

Seed Demand Forecasting

Wind Speed Forecasting

Temperature Forecasting

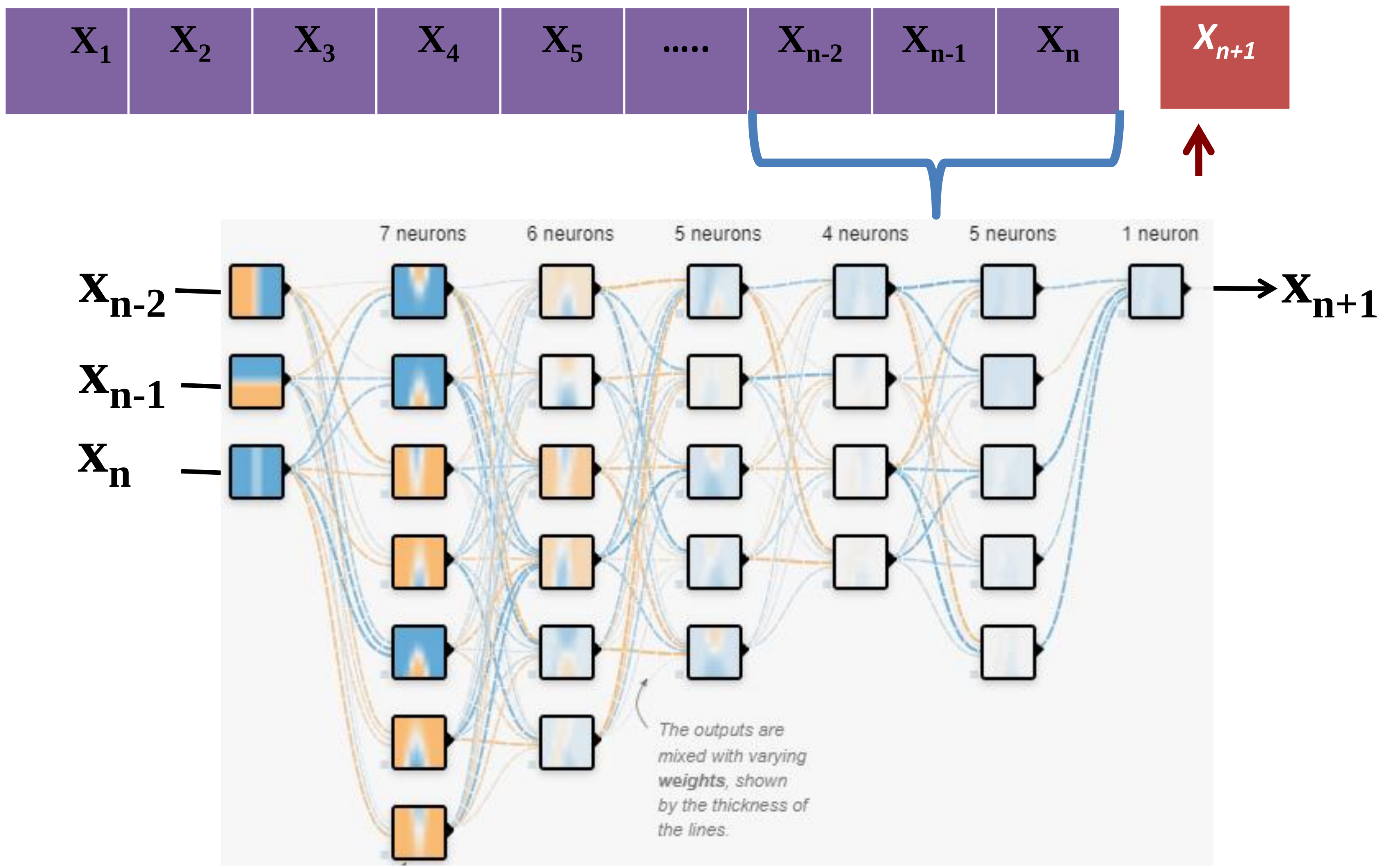
:

:

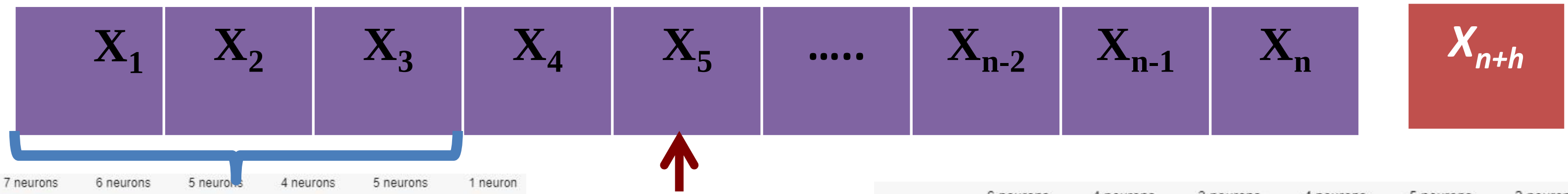
:

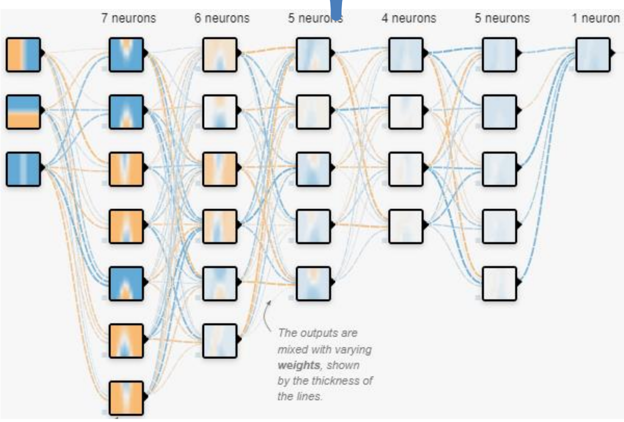
How to use Deep Learning Models in TSF

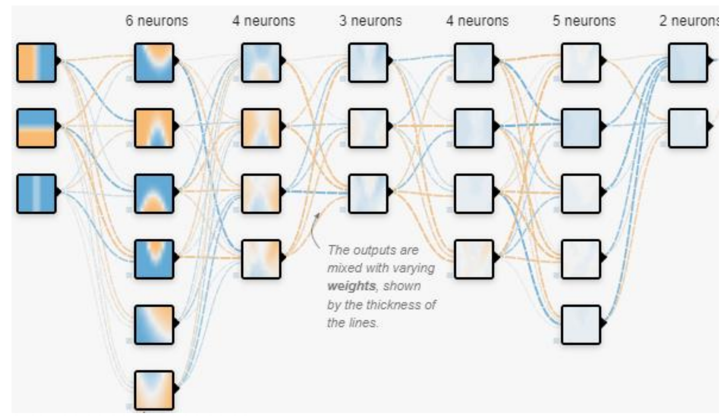
How Deep Neural Network in TSF



How Deep Neural Network for Multi-Step Ahead TSF







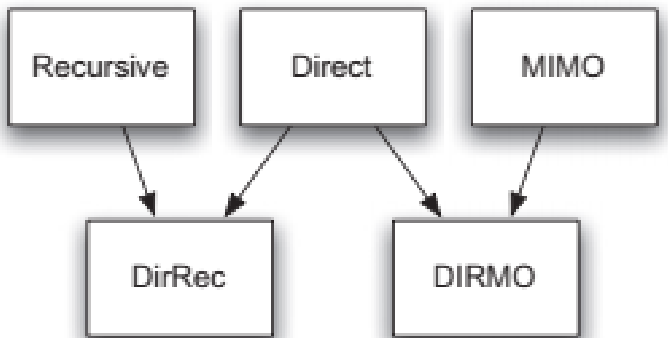


Fig. 1. The different forecasting strategies with the links showing their relationship.

Taieb, S. B., Bontempi, G., Atiya, A. F., & Sorjamaa, A. (2012). A review and comparison of strategies for multi-step ahead time series forecasting based on the NN5 forecasting competition. *Expert systems with applications*, *39*(8), 7067-7083.

Time Series Forecasting using Machine Learning Models

The number of significant inputs *k* of DL models will be determined by analyzing the autocorrelation and partial autocorrelation function of the time series.

↓

The time series will be pre-processed (Normalization, Treatment of Trend and Seasonal Components).

↓

The time series of length *n* will be transformed to *n*-*k* patterns using sliding window technique. Then the patterns will be splitted into Train, Validation and Test Sets.

↓

Using the Train and Validation set determine the ML model parameters. Once the model parameters are determined, the forecasts on Test set are computed using the obtained model parameters.

↓

Denormalize, Detrend and Deseasonalize the computed forecasts to obtain the true forecasts.

↓

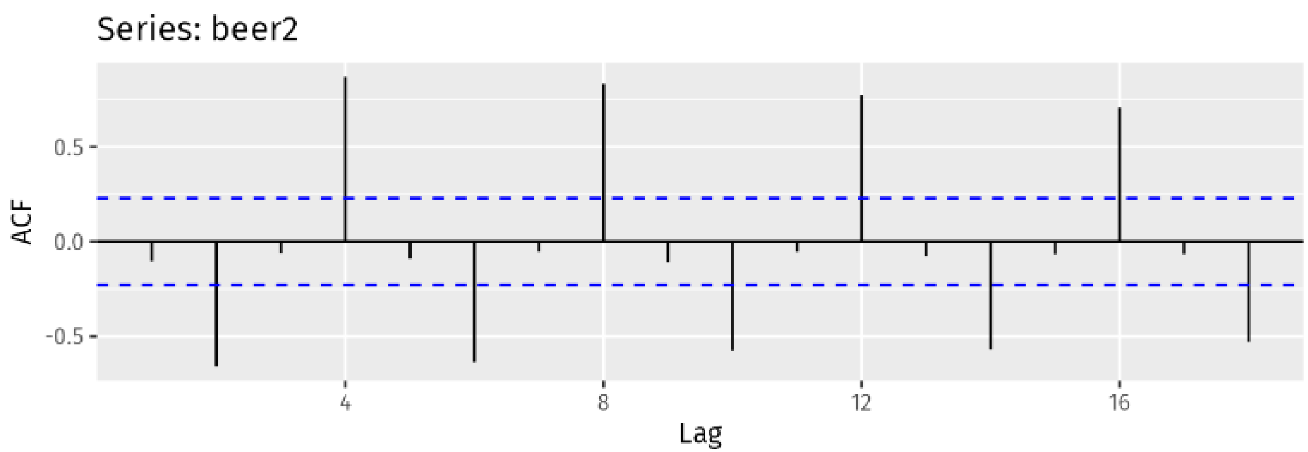
Measure the forecasting accuracy.

Time Series Forecasting using Machine Learning Models

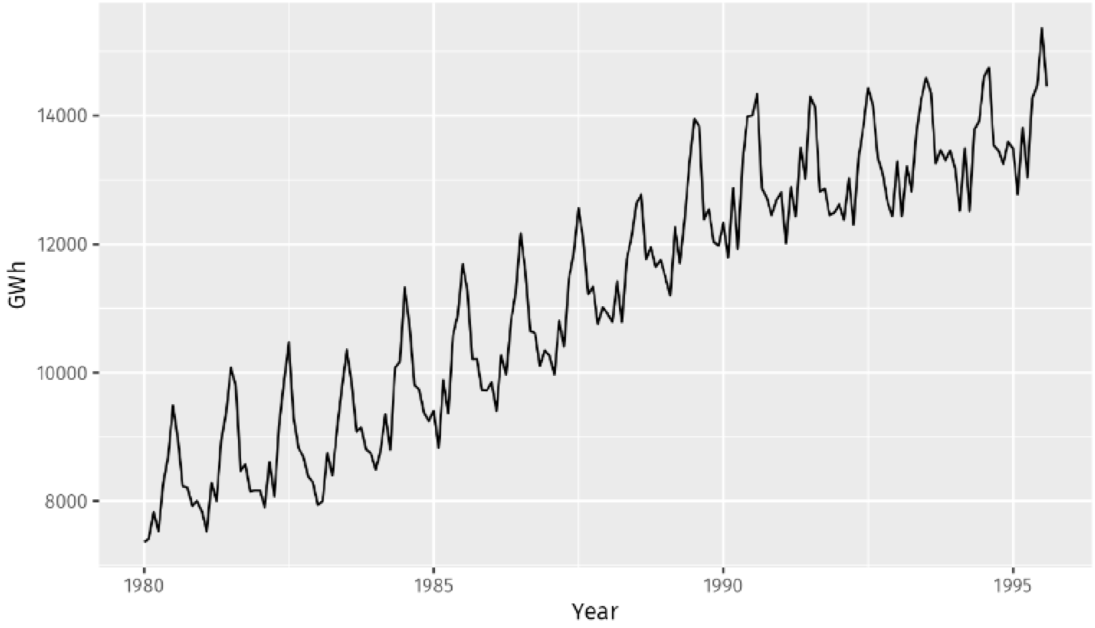
- Just as correlation measures the extent of a linear relationship between two variables, autocorrelation measures the linear relationship between *lagged values* of a time series.

- There are several autocorrelation coefficients, corresponding to each panel in the lag plot. For example, r_1 measures the relationship between y_t and y_{t-1}, r_2 measures the relationship between y_t and y_{t-2}, and so on.

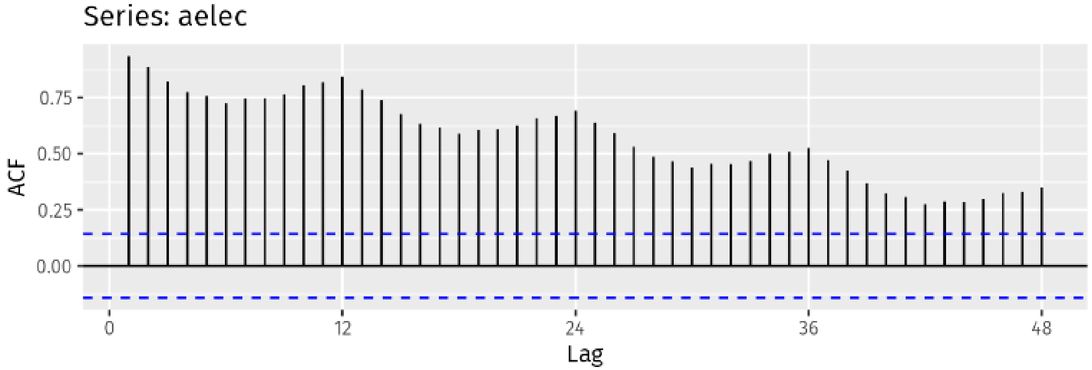
- The value of r_k can be written as $r_k = \frac{\sum_{i=k+1}^{n}(y_i-\bar{y})(y_{i-k}-\bar{y})}{\sum_{i=k+1}^{n}(y_i-\bar{y})^2}$



Time Series Forecasting using Machine Learning Models



Monthly Australian electricity demand from 1980–1995.



ACF of monthly Australian electricity demand.

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↓

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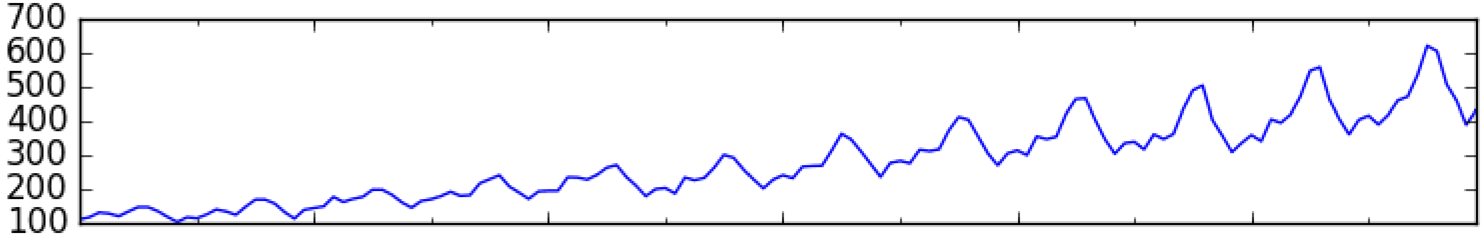
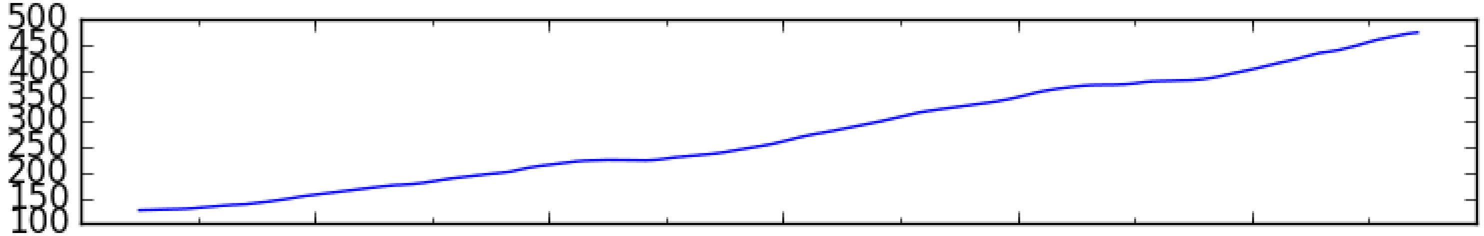
Motivation for Hybrid Models

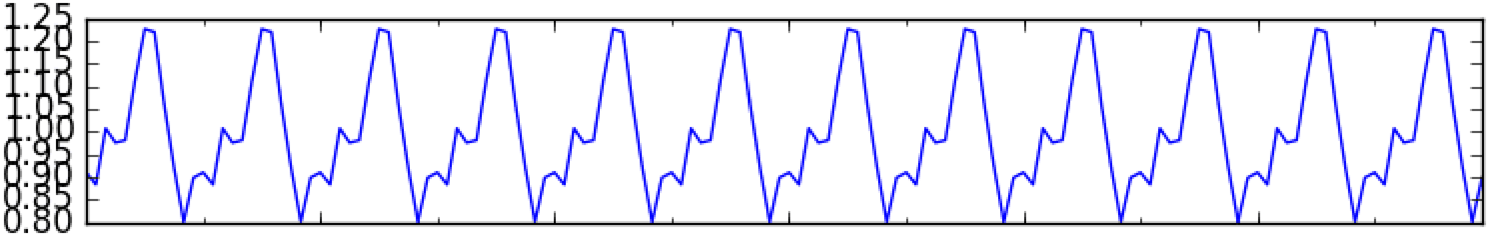
Real-world time series may not be purely linear or purely nonlinear. Rather it contains a combination of linear and nonlinear components.



Original Time Series



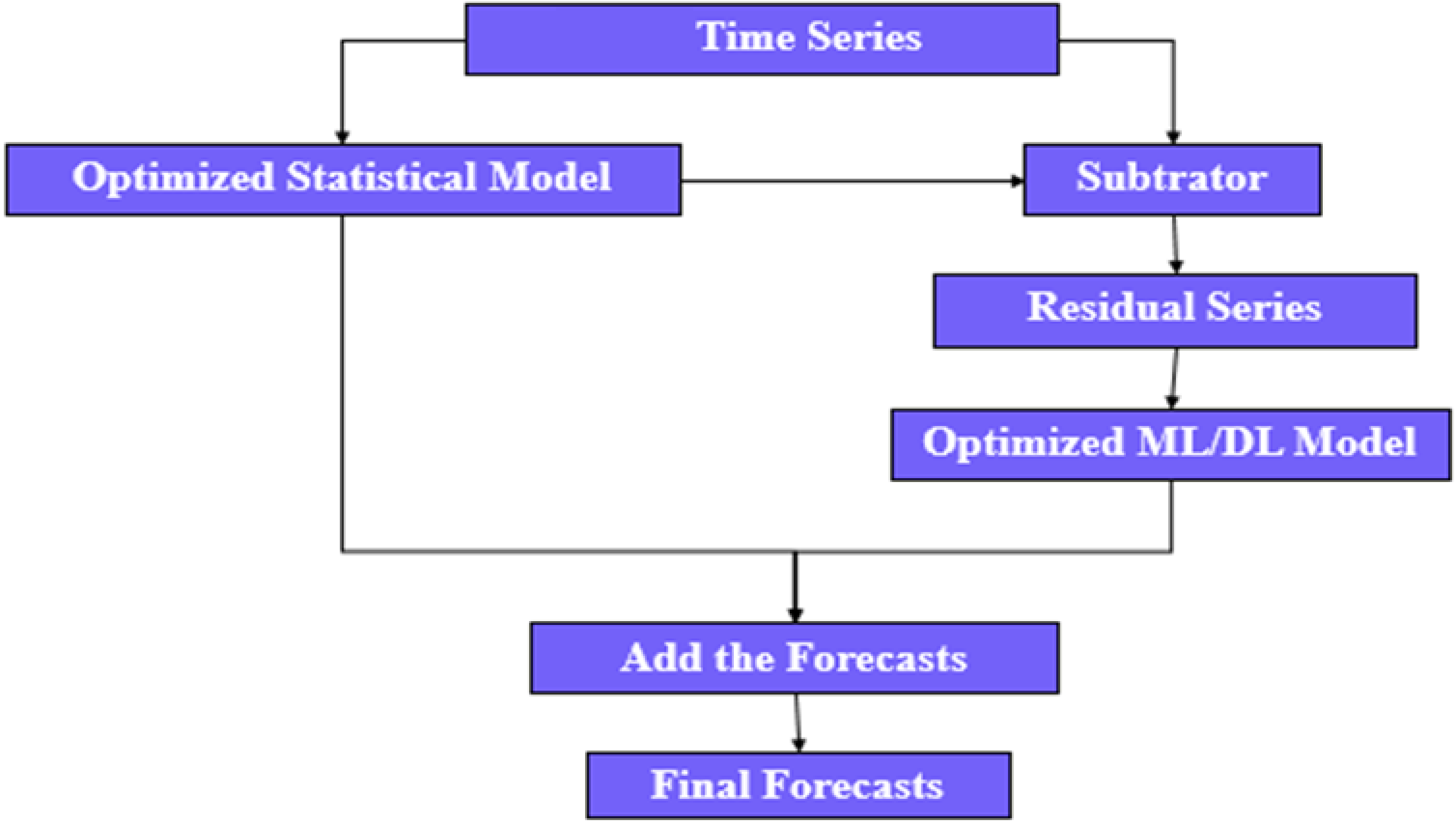
Linear Component



Nonlinear Component

Time Series Forecasting using Optimized Series Hybrid Models

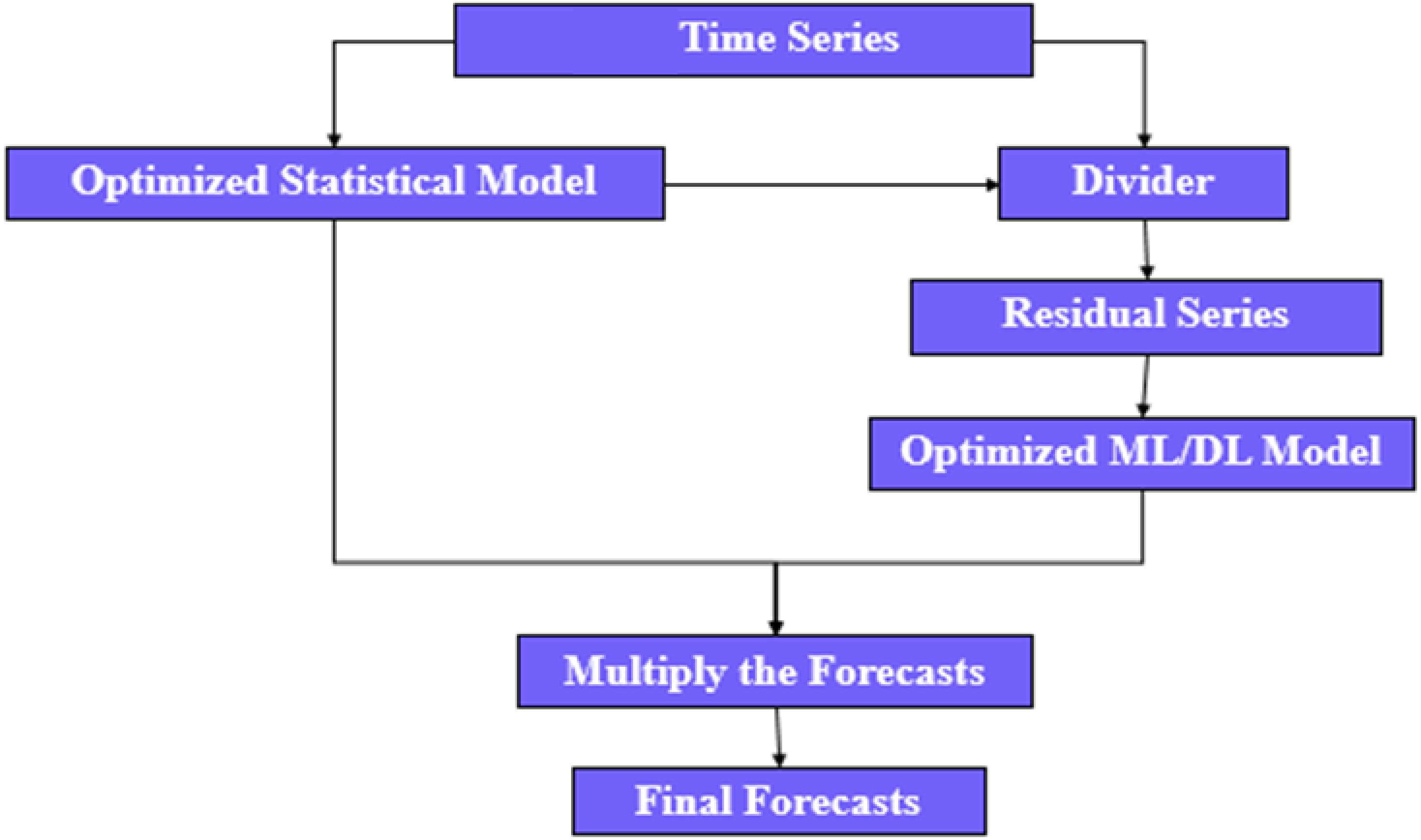
Additive Hybrid Model



Sourav Kumar Purohit, and **Sibarama Panigrahi***. "Novel Deterministic and Probabilistic Forecasting Methods for Crude Oil Price employing Optimized Deep Learning, Statistical and Hybrid Models." *Information Sciences*, vol. 658, 120021 (2024). **[Elsevier, IF:8.1, SCI]**

Time Series Forecasting using Optimized Series Hybrid Models

Multiplicative Hybrid Model



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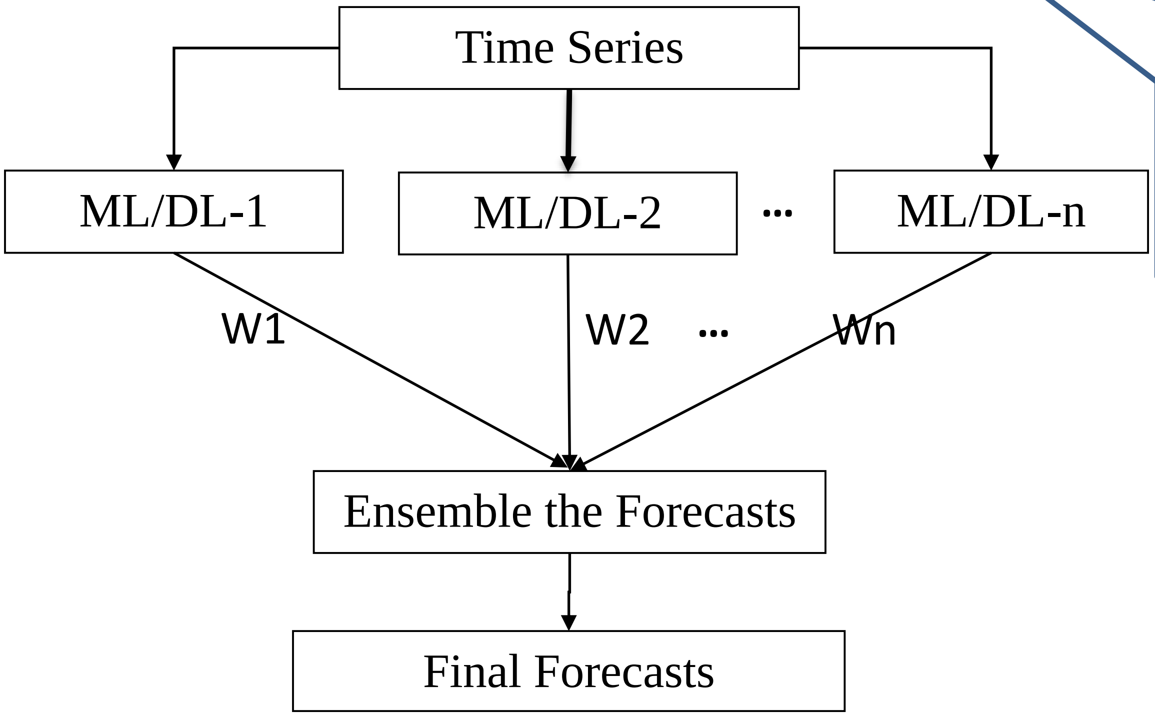
Time Series Forecasting using Optimized Parallel Hybrid Models

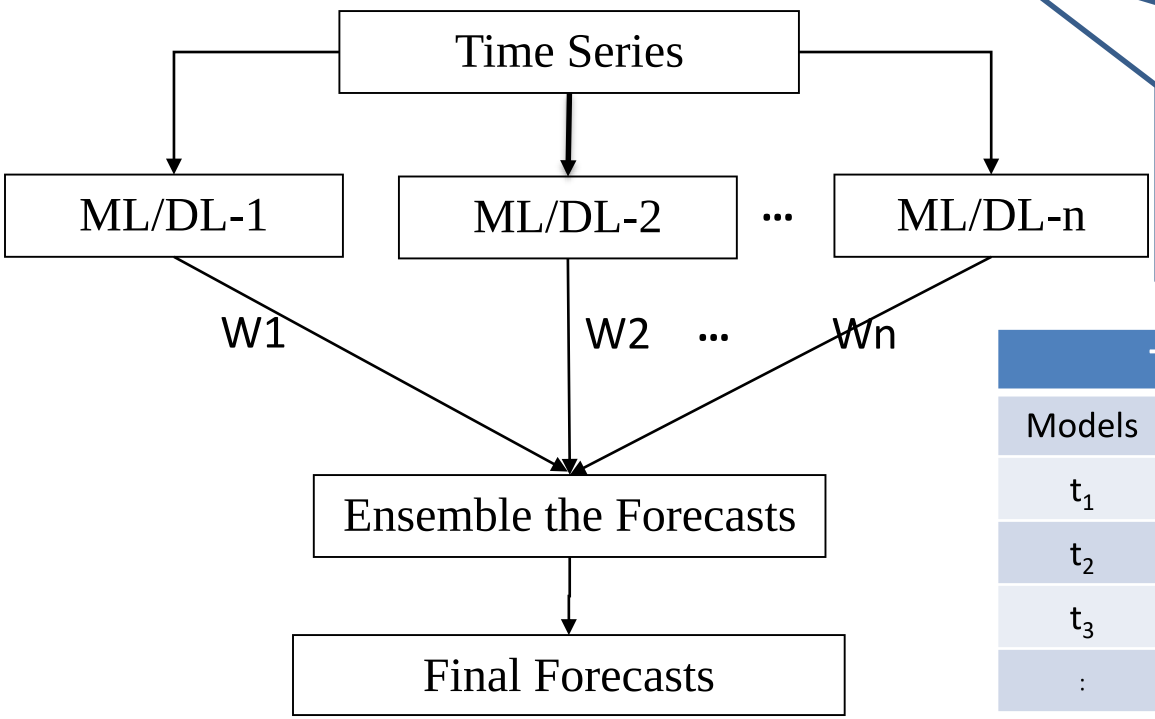
Parallel Hybrid Model



1. Equal Weight
2. Variable Weight
3. Time-Varying Weight

Time Series Forecasting using Optimized Parallel Hybrid Models

Parallel Hybrid Model



1. Equal Weight
2. Variable Weight
3. Time-Varying Weight

Time-Varying Weight			
Models	F_1	F_2	F_3
t_1	0.1	0.3	0.6
t_2	**0.2**	**0.2**	**0.6**
t_3	0.15	0.35	0.5
:	:	:	:

Equal Weight			
Models	F_1	F_2	F_3
Weight	0.33	0.33	0.33
Final Forecast	$F=0.33*F_1+0.33*F_2+0.33*F_3$		

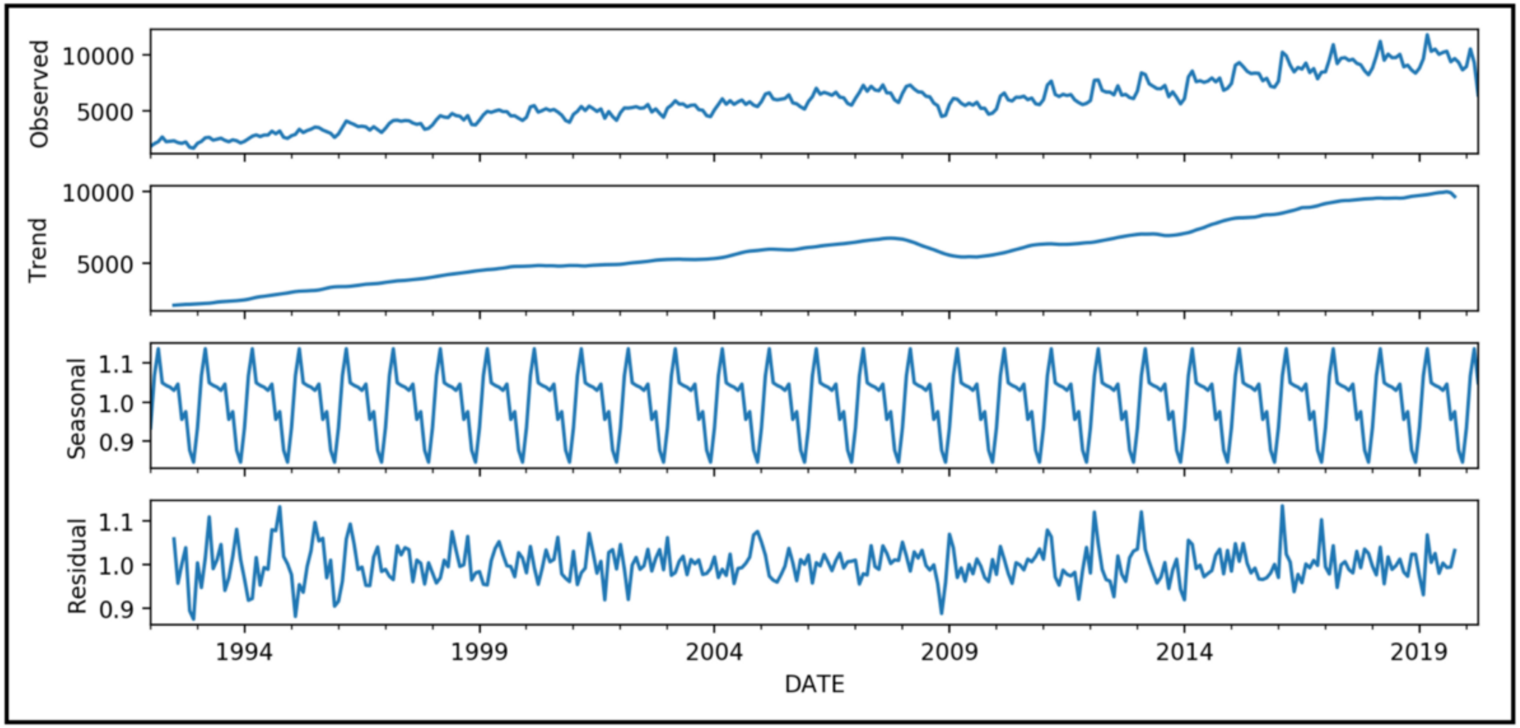
Variable Weight			
Models	F_1	F_2	F_3
Weight	**0.1**	0.3	**0.6**
Final Forecast	$F=0.1*F_1+0.3*F_2+0.6*F_3$		

Motivation for Decomposition Based Hybrid Models

Blind application of a linear (statistical) or nonlinear (ML/DL) model to a time series containing both linear and/or nonlinear patterns may not be appropriate.

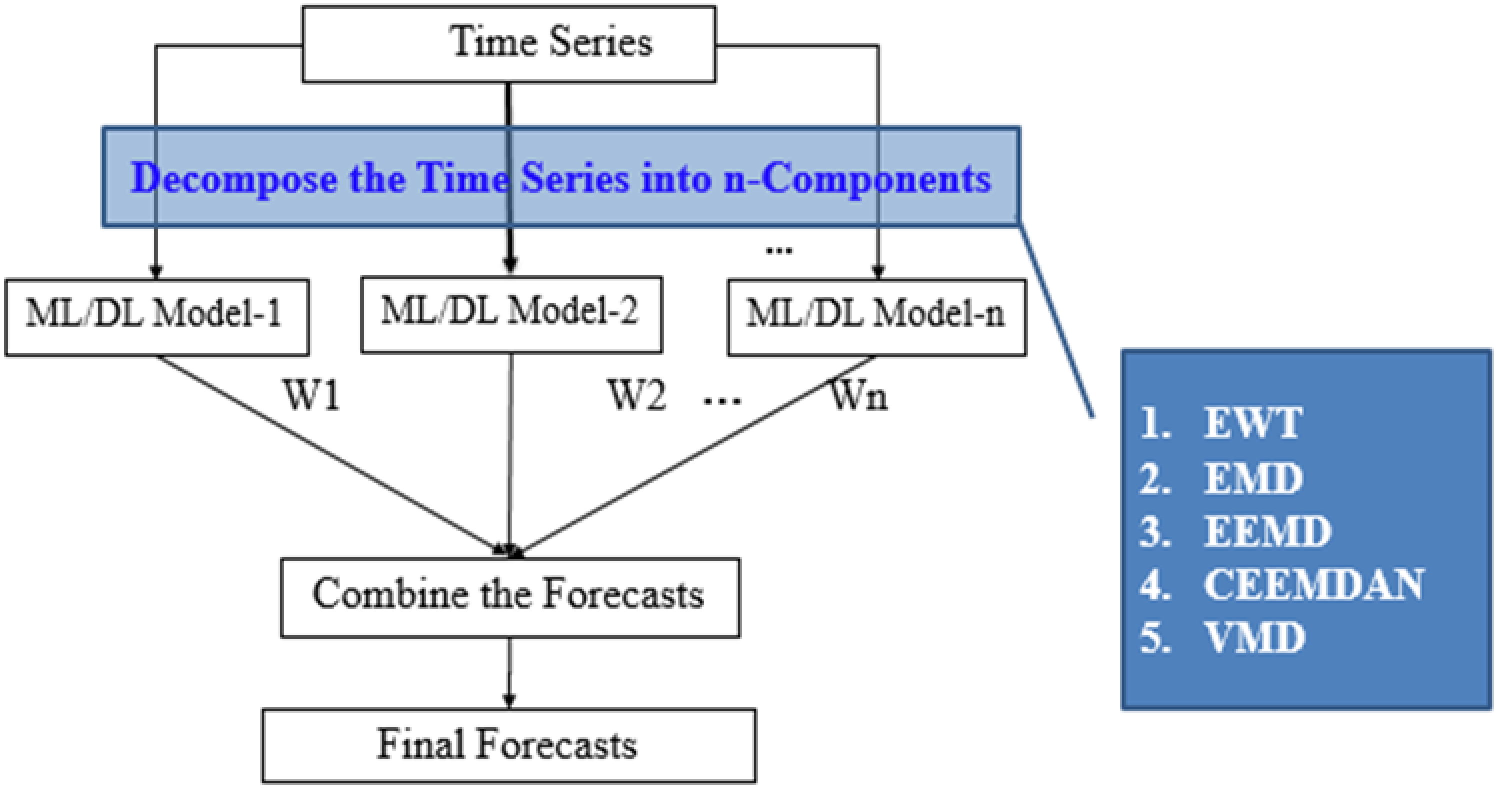
First Decompose the time series and then model individual components based on its characteristics.

Decomposition can also be based on Error(Residual), Trend and Seasonal Components. It may be again additive or multiplicative.



Time Series Forecasting using Optimized Decomposition Based Hybrid Model

Decomposition Based Hybrid Model



Published Papers

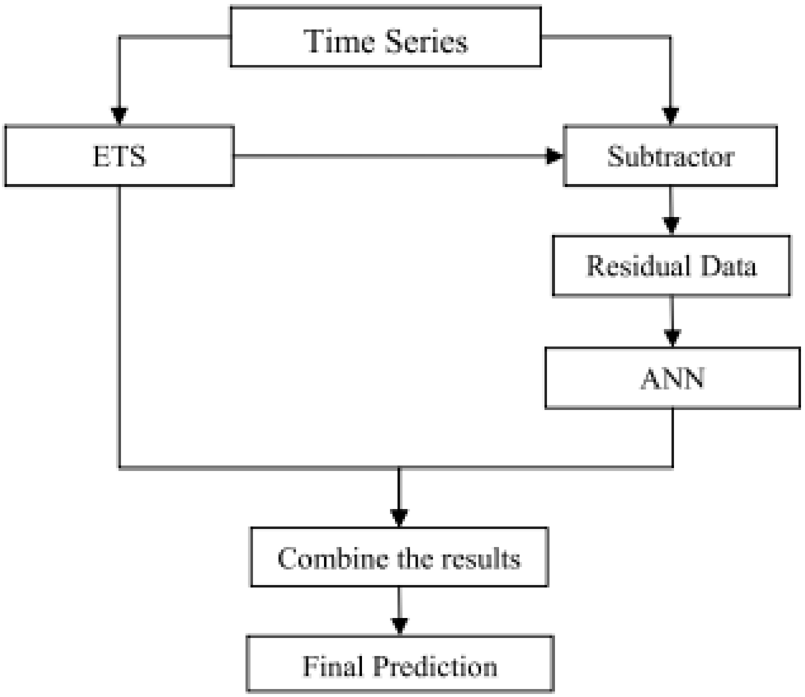
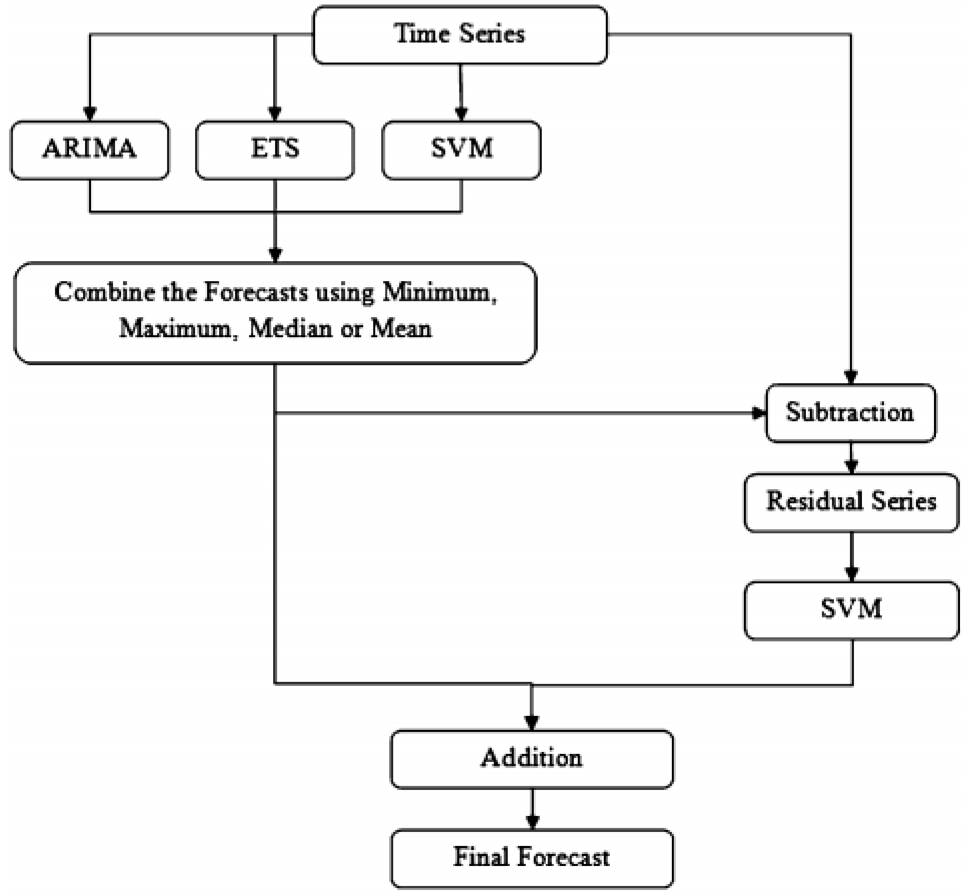


Fig. 2. Proposed methodology.

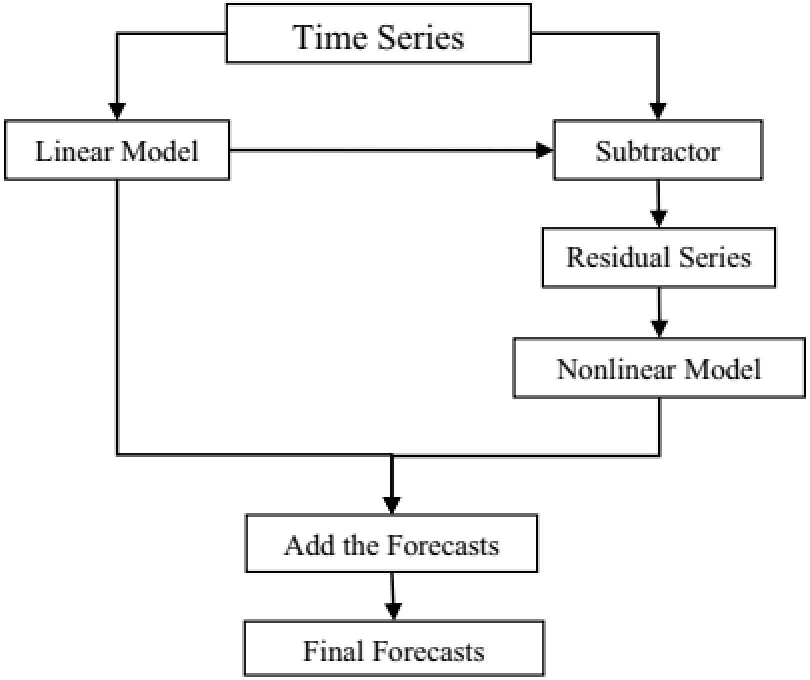
Sibarama Panigrahi, and Himansu Sekhar Behera. "A hybrid ETS–ANN model for time series forecasting." Engineering Applications of Artificial Intelligence 66 (2017): 49-59. ISSN: 0952-1976 **[Elsevier, IF:7.80, SCI]**

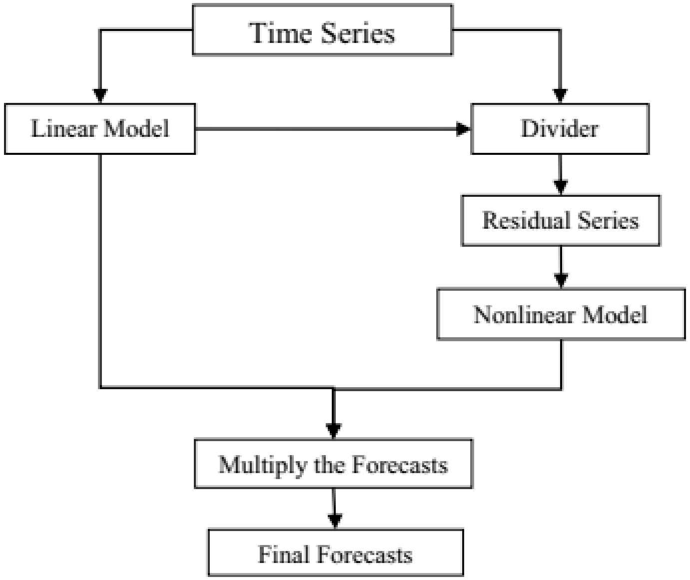
Published Papers



Sibarama Panigrahi*, Radha Mohan Pattanayak, Prabira Kumar Sethy, Santi Kumari Behera. "Forecasting of Sunspot Time Series Using a Hybridization of ARIMA, ETS and SVM Methods." Solar Physics 296.1 (2021): 1-19. **[Springer, IF:2.96, SCI]**

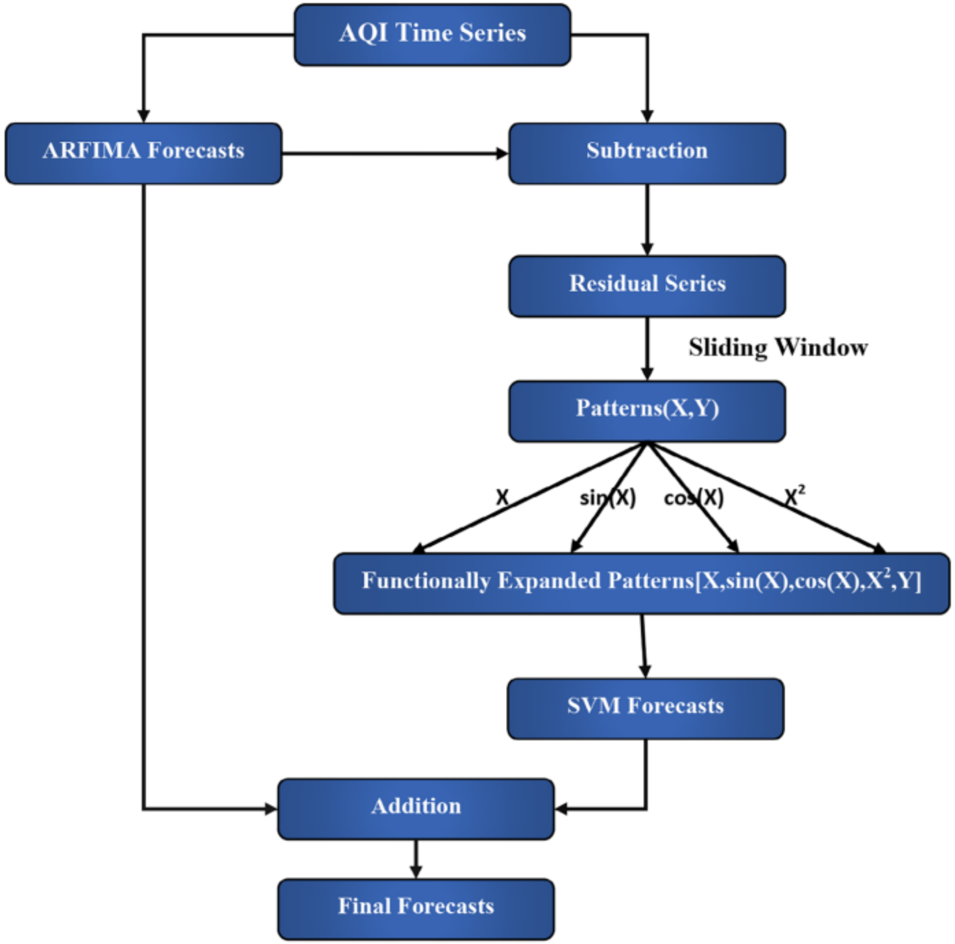
Published Papers





Sourav Kumar Purohit, **Sibarama Panigrahi***, Prabira Kumar Sethy, and Santi Kumari Behera. "Time series forecasting of price of agricultural products using hybrid methods." Applied Artificial Intelligence (2021), vol. 35, no. 15, pp. 1388-1406. **[Taylor & Francis, IF:2.78, SCI]**

Published Papers



S. S. Pradhan, **Sibarama Panigrahi***, S. K. Purohit, and J. Dash. "Study and development of hybrid and ensemble forecasting models for air quality index forecasting." Expert Systems (2023). **[Wiley, IF: 3.3, SCI]**

INTRODUCTION TO FUZZY TSF

- **Intuition behind Fuzzy Time Series Forecasting:**

Temperature Time Series: 5, 11, 17, 23, 29, 32, 42, 45
Universe of Discourse: [5-5 - 45+5] = [0-50]

Temperature Time Series: 5, 11, 17, 23, 29, 28, 32, 45
Fuzzy Time Series: 0, 1, 1, 2, 2, 2, 3, 4

Identify the Order of the fuzzy TSF Model: (Let 2)

Convert the fuzzy time series into Fuzzy Logical Relationships

0, 1 → 1
1, 1 → 2
1, 2 → 2
2, 2 → 2
2, 2 → 3   2,2 →2,3
2, 3 → 4

Linguistic Variable	Interval	Interval Index	Mid-Point
Very Cold	0-10	0	5
Cold	11-20	1	15
Normal	21-30	2	25
Hot	31-40	3	35
Very Hot	41-50	4	45

Model the Fuzzy Logical Relationships using Optimized DL Models and Forecast the fuzzy future values.

Fuzzified Forecasts: 2, 3, 3, 4, 4
Defuzzify Forecasts: 25, 35, 35, 45, 45

FUZZY TIME SERIES FORECASTING USING ML MODELS

The universe of the discourse of the time series will be determined which will be divided into a number of intervals.

↓

Fuzzify the Time Series by exchanging each observation of the time series by the index of the belonging interval of the observation.

↓

The order of the fuzzy TSF model will be determined by using the autocorrelation and partial autocorrelation function of the fuzzy time series (FTS)

↓

The Fuzzy Logical Relationships (FLRs) will be established and modeled using the aforementioned ML/DL models.

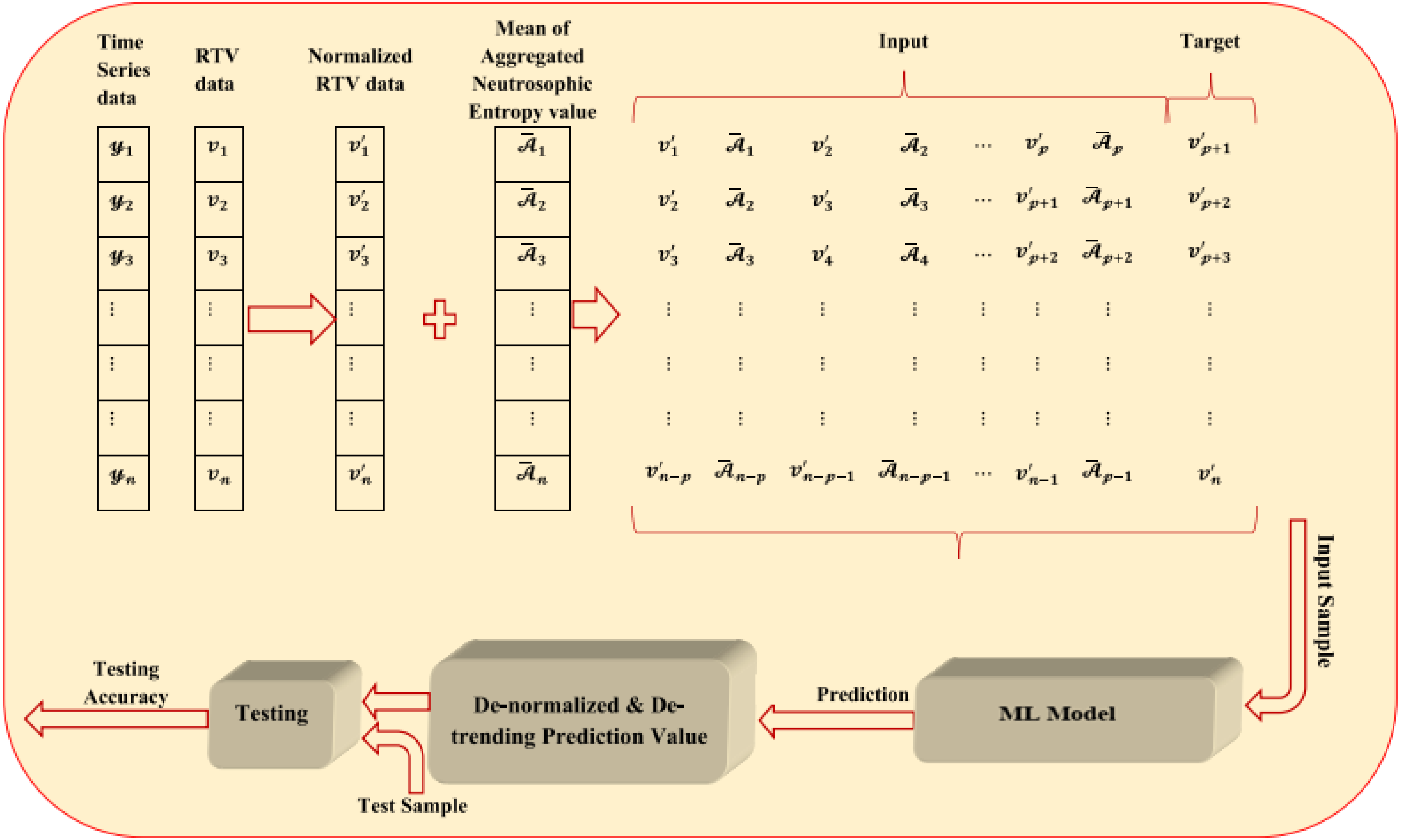
↓

Defuzzify and measure the forecasting accuracy.

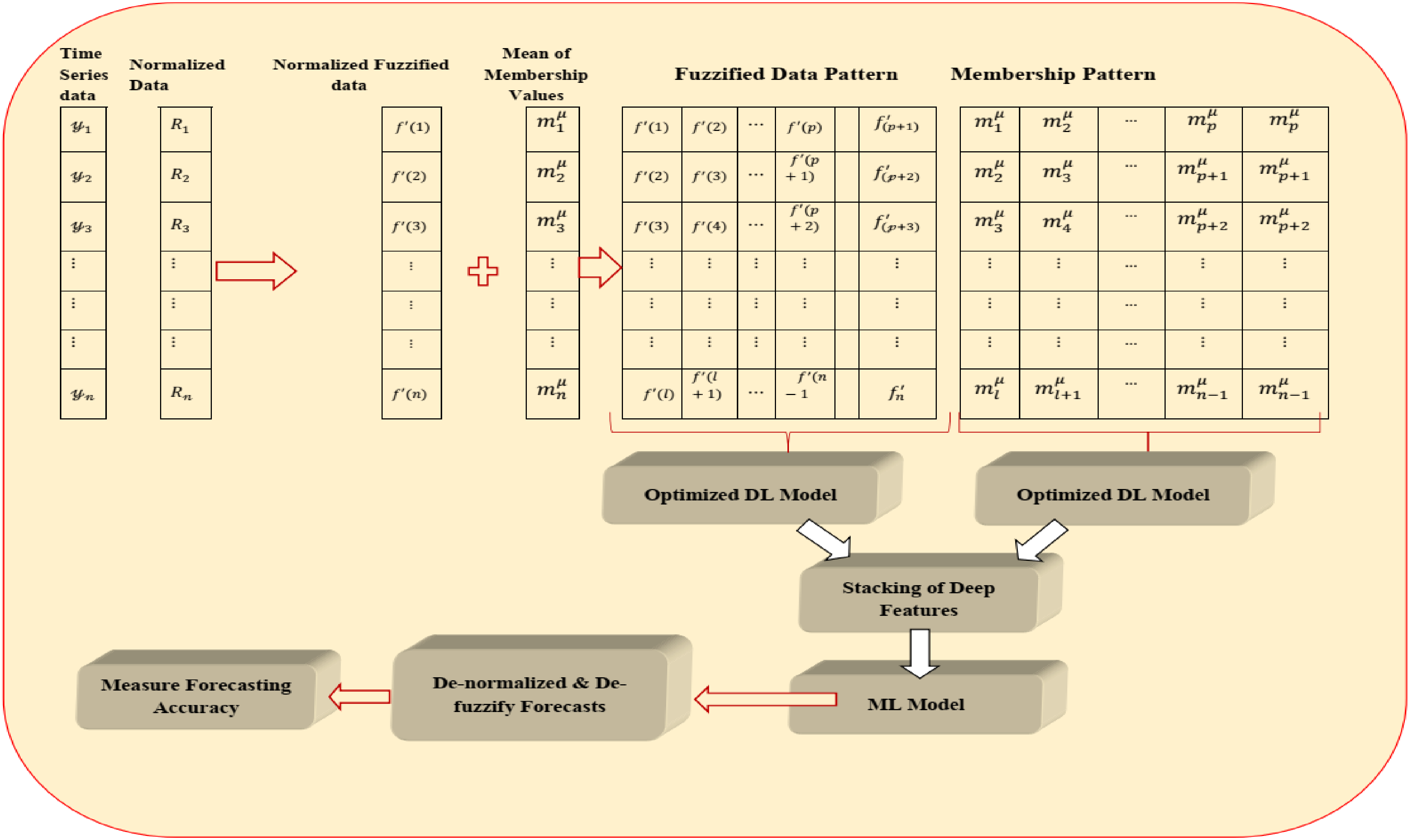
Fuzzy Time Series Forecasting using ML Models

- **Key Factors affecting the efficiency of Fuzzy Time Series Forecasting Methods:**
  - **Partitioning of Universe of Discourse**
    - **Equal-Length Partitioning Methods**
      - » **Average-Based Methods**
      - » **Modified Average-Based Methods**
      - » **Ratio-Based Methods**
    - **Variable-Length Partitioning Methods**
      - » **Cumulative Probability Distribution Approach**
      - » **Using Swarm and Evolutionary Algorithms**
      - » **Using Fuzzy-C-Means Clustering**
  - **Modelling of Fuzzy Logical Relationships**
    - **Using Rule based methods**
    - **Using Optimized ML/DL models**
    - **Using Hybrid Models**
  - **Fuzzification and Defuzzification Methods**
  - **Type of Fuzzy Set**
  - **Consideration or Non-Consideration of Membership Values**
  - **Type of Membership Function used.**

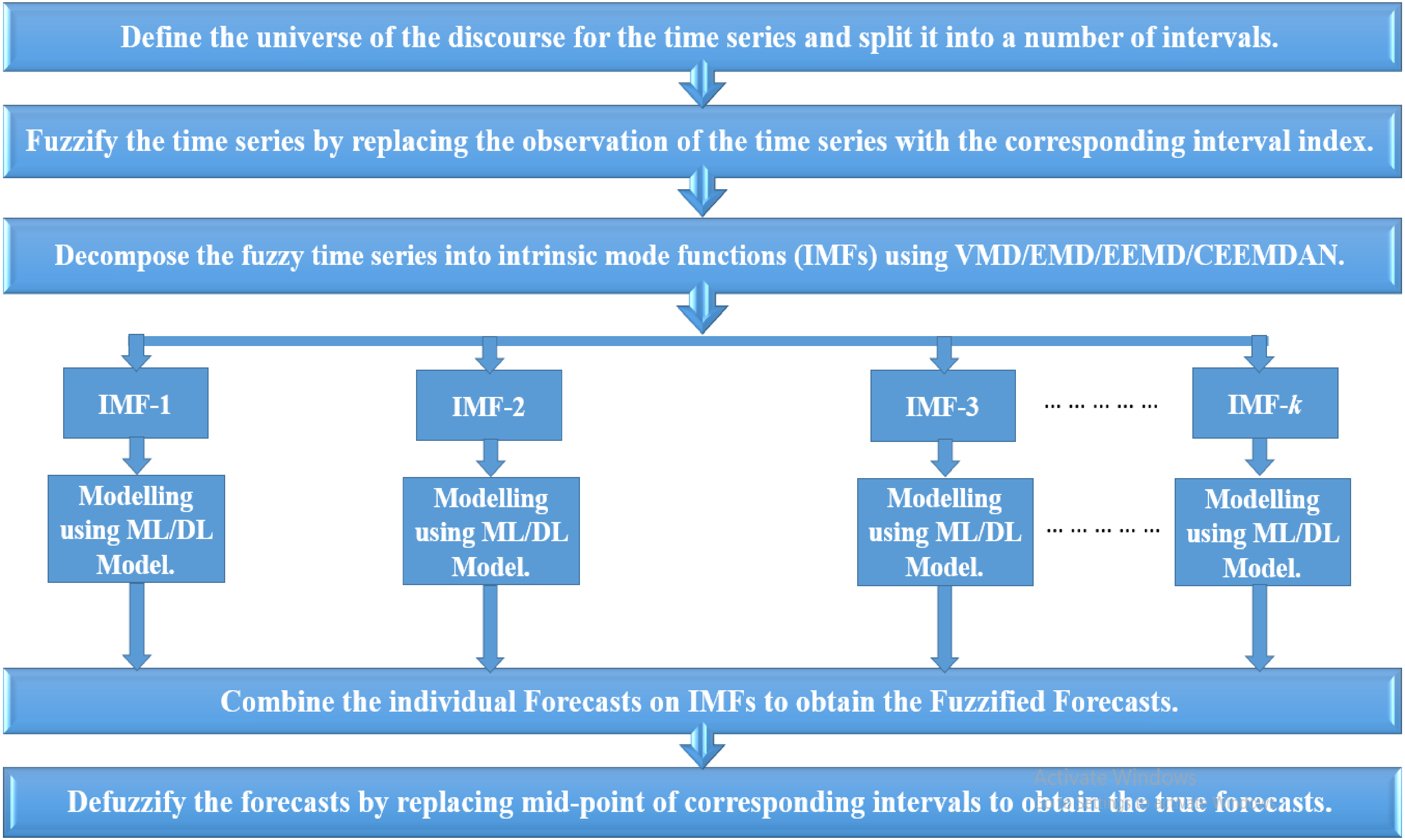
Fuzzy Time Series Forecasting using Machine Learning Models



Fuzzy Time Series Forecasting using Machine Learning Models



Fuzzy Time Series Forecasting using Machine Learning Models



Fuzzy Time Series Forecasting using Machine Learning Models

Fuzzy Time Series Forecasting using different fuzzy sets:

- **Traditional Fuzzy Set** (Considers only membership value)
- **Intuitionistic Fuzzy Set** (Considers membership and non-membership value)
- **Hesitant Fuzzy Set** (Considers dependent membership, non-membership and hesitation value)
- **Neutrosophic Fuzzy Set** (Considers independent membership, non-membership and hesitation value)
- :
- :

Published Papers

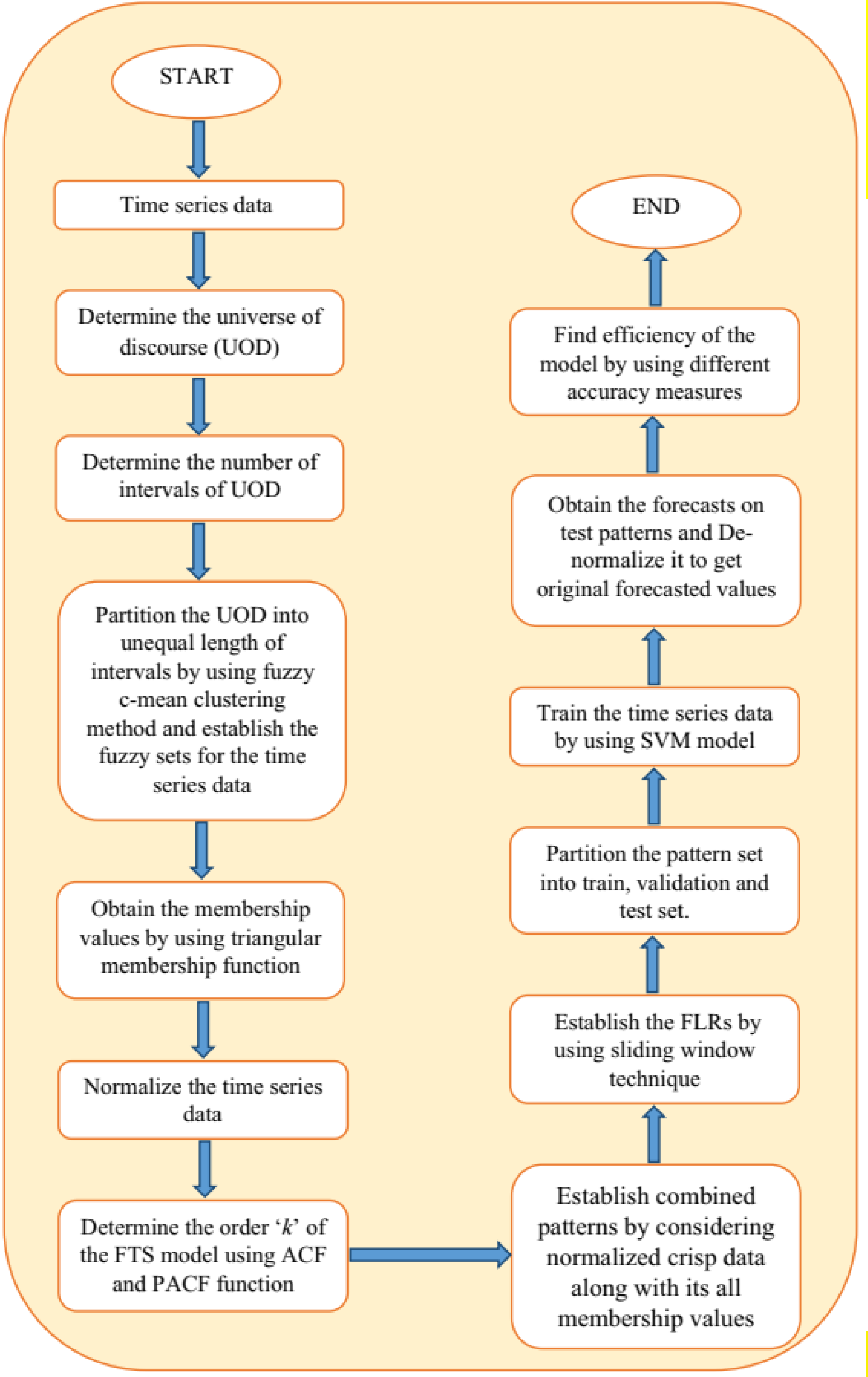
1. **Sibarama Panigrahi**, and Himansu Sekhar Behera. "A study on leading machine learning techniques for high order fuzzy time series forecasting." Engineering Applications of Artificial Intelligence 87 (2020): 103245. **[Elsevier, IF: 7.80, SCI]**

Algorithm 1: FTSF-DBN, FTSF-LSTM and FTSF-SVM Methodology

Input the time series (y), length of train set (l_{tr}), length of validation set (l_v)
//Define the universe of discourse $U = [U_l \;\; U_h]$ and partition U into equal length intervals
$D = 0.2 \times (\max(y_{l_{tr}+l_{tv}}) - \min(y_{l_{tr}+l_{tv}}))$
$U_l = \min(y_{l_{tr}+l_{tv}}) - D$
$U_h = \max(y_{l_{tr}+l_{tv}}) + D$
Sort the time series
Delete the duplicate elements from the sorted time series (y')
Compute the absolute first differenced series (y'_{diff})
Compute the half of the average of y'_{diff} and set it to length
Compute the base for round off
Compute the length of interval l by rounding off the length by base
Using l as length of interval, divide the universe of discourse $U = \{u_1, u_2, u_3 \dots u_w\}$ into q equal length intervals with $w = (U_h - U_l)/l$
Compute the mid-point m_i of the intervals u_i.
// Fuzzify the time series data
for j=1 to n
  if y_j belongs to the partition u_i
    $f_j(t) = i$
  end if
end for
// Establish fuzzy logical relationships using DBN, LSTM or SVM
Normalize the fuzzified time series $f(t)$ to obtain $f'(t)$.
Determine the order k of fuzzy TSF model
Transform the $f'(t)$ into a n-k patterns using sliding window protocol
Divide the patterns into train, validation and test patterns
Using the train and validation patterns determine the parameters of DBN, SVM or LSTM
Obtain the forecasts $\widehat{f}'(t)$ using the optimized parameters of DBN, SVM or LSTM
Denormalize and round off $\widehat{f}'(t)$ to obtain $\hat{f}(t)$
// Defuzzify and measure the forecast accuracy
for each element $\widehat{f}_i(t)$ in $\hat{f}(t)$
  if $\widehat{f}_i(t) < 1$
    $\hat{y}_i = m_1$
  else if $\widehat{f}_i(t) > q$
    $\hat{y}_i = m_q$
  else
    $\hat{y}_i = m_{\widehat{f}_i(t)}$
  end if
end for
Compute the forecasting accuracy using y and $\hat{y}$

Published Papers

2. Radha Mohan Pattanayak, **Sibarama Panigrahi,** and H. S. Behera. "High-order fuzzy time series forecasting by using membership values along with Data and Support Vector Machine." Arabian Journal for Science and Engineering 45.12 (2020): 10311-10325. ISSN: 2191-4281 **[Springer, IF:2.81, SCI]**



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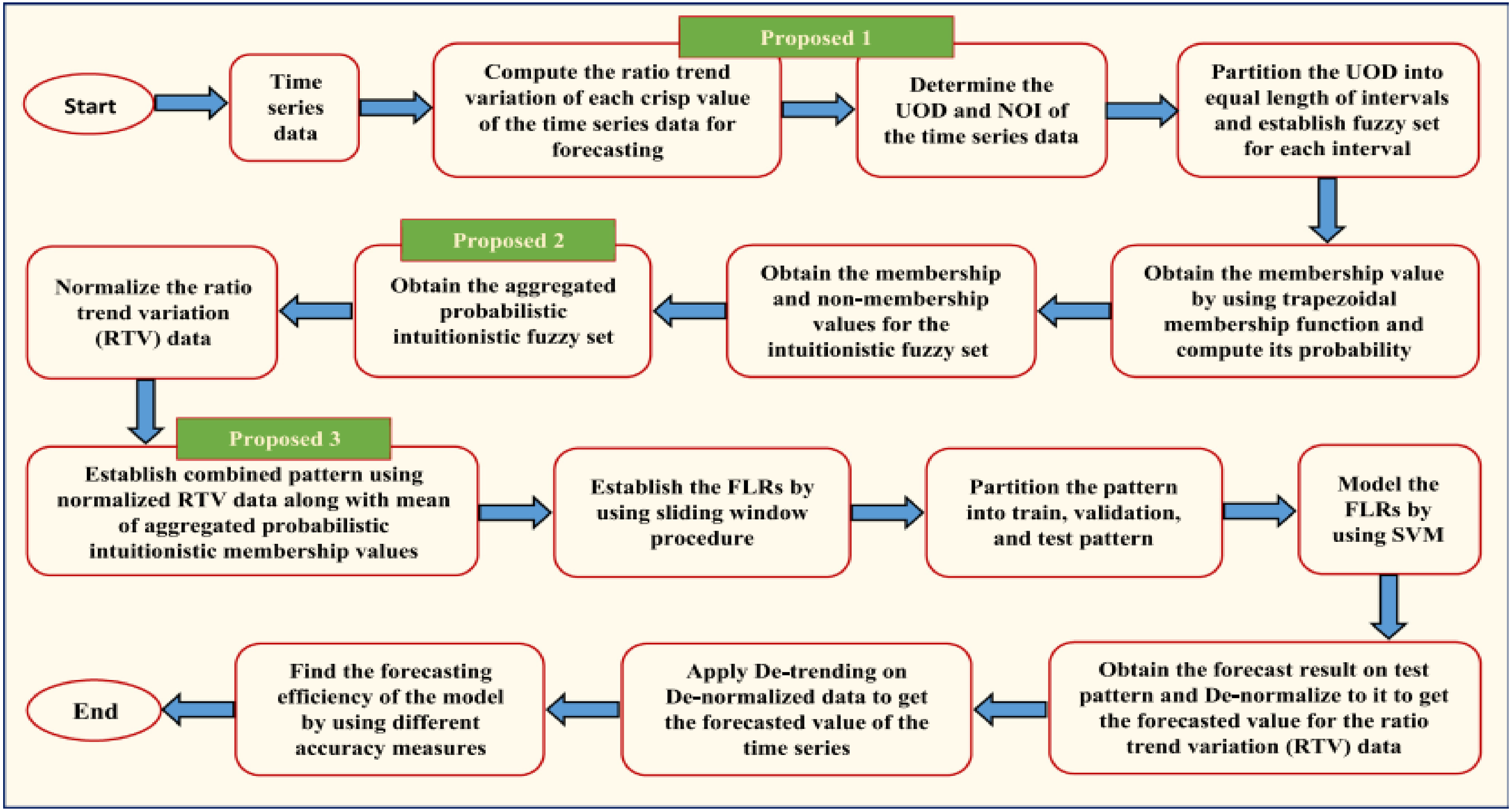

3. Radha Mohan Pattanayak, H. S. Behera, and **Sibarama Panigrahi**. "A novel probabilistic intuitionistic fuzzy set based model for high order fuzzy time series forecasting." Engineering Applications of Artificial Intelligence 99 (2021): 104136. ISSN: 0952-1976 **[Elsevier, IF:7.80, SCI]**

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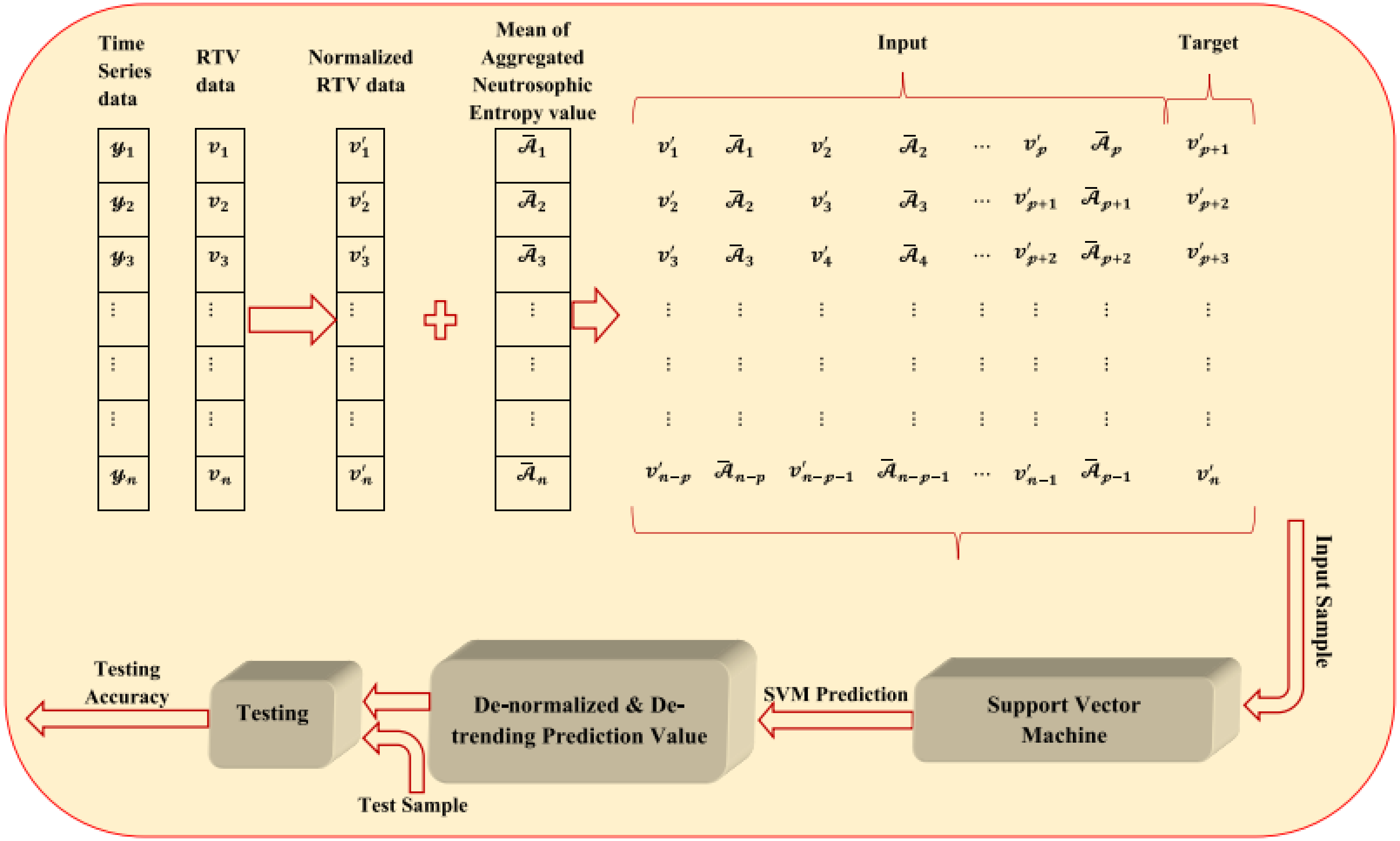

4. Radha Mohan Pattanayak, H. S. Behera, and **Sibarama Panigrahi**. "A non-probabilistic neutrosophic entropy-based method for high-order fuzzy time-series forecasting." Arabian Journal for Science and Engineering vol. 47, no. 2 (2022): 1399-1421. **[Springer, IF:2.81, SCI]**

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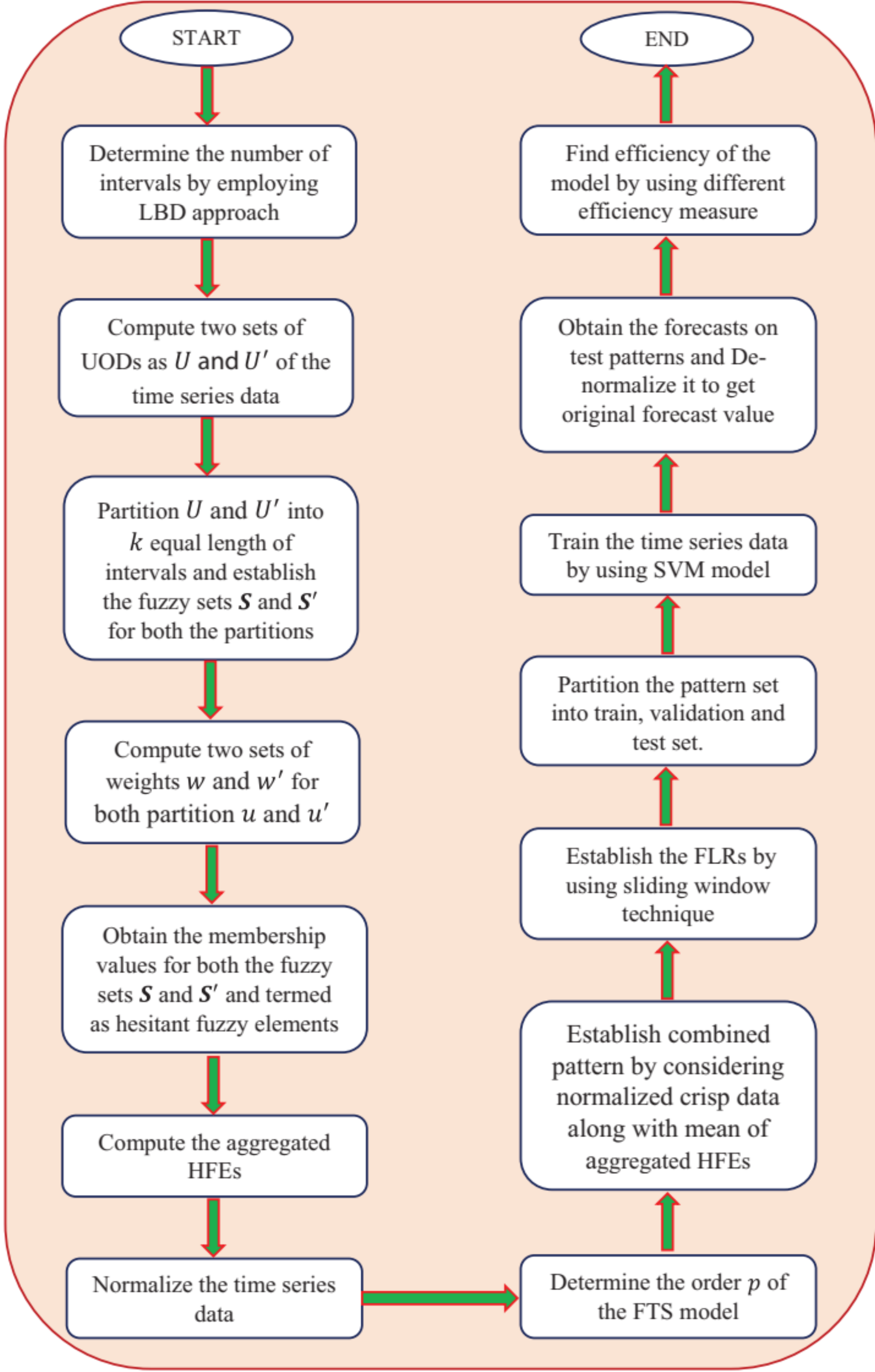
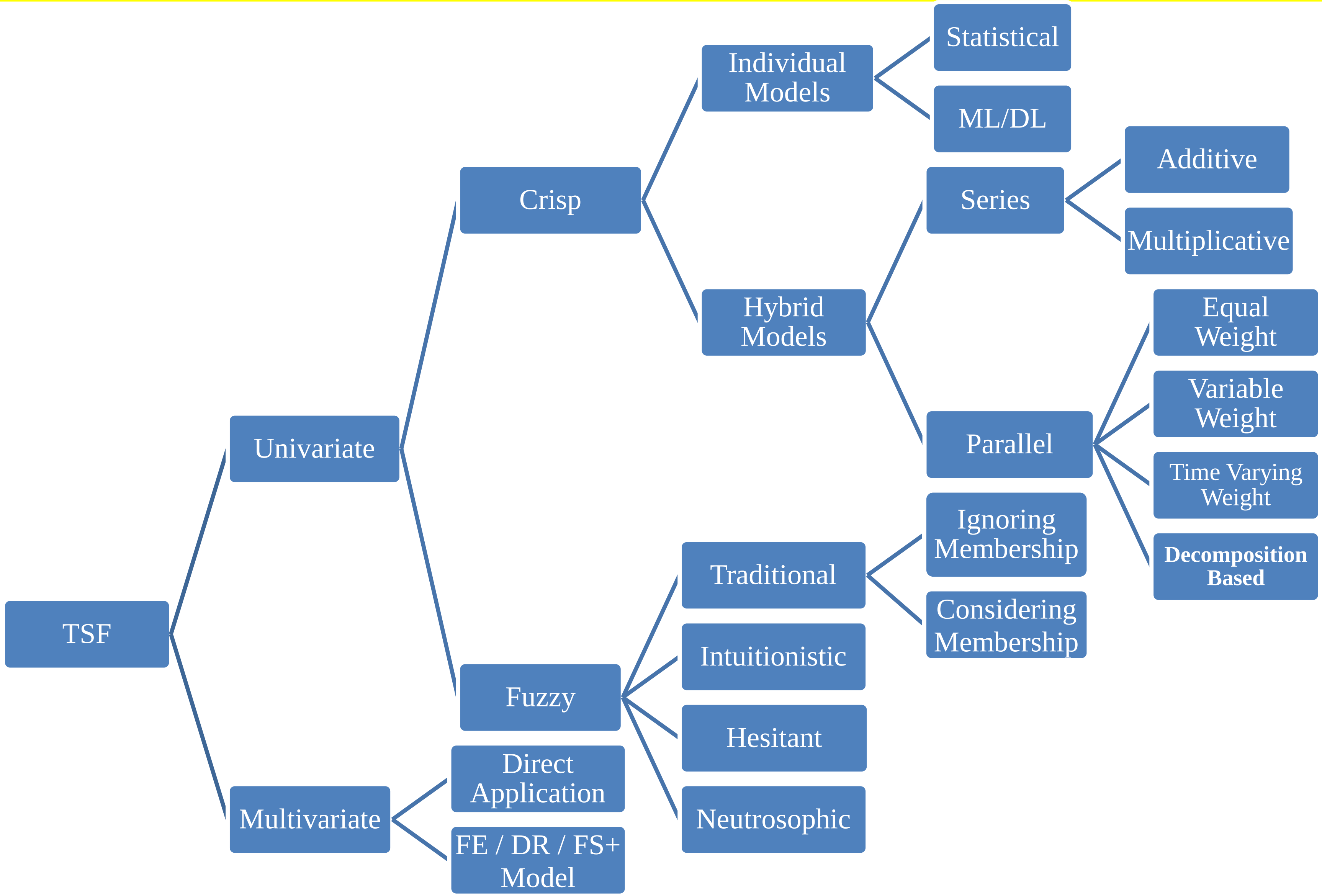
5. Radha Mohan Pattanayak, Himansu Sekhar Behera, and **Sibarama Panigrahi**. "A Novel High Order Hesitant Fuzzy Time Series Forecasting by using mean Aggregated Membership value with Support Vector Machine." Information Sciences (2023). **[Elsevier, IF: 8.01, SCI]**



Time Series Forecasting (TSF) Techniques [Classification]



RELATED PUBLICATIONS [CRISP TIME SERIES FORECASTING]

1. **Sibarama Panigrahi**, and Himansu Sekhar Behera. "A hybrid ETS–ANN model for time series forecasting." Engineering Applications of Artificial Intelligence 66 (2017): 49-59. ISSN: 0952-1976 **[Elsevier, IF:7.80, SCI]**
2. **Sibarama Panigrahi**, and Himansu Sekhar Behera. "Time Series Forecasting Using Differential Evolution-Based ANN Modelling Scheme." Arabian Journal for Science and Engineering 45.12 (2020): 11129-11146. ISSN: 2191-4281 **[Springer, IF:2.81, SCI]**
3. **Sibarama Panigrahi***, Radha Mohan Pattanayak, Prabira Kumar Sethy, Santi Kumari Behera. "Forecasting of Sunspot Time Series Using a Hybridization of ARIMA, ETS and SVM Methods." Solar Physics 296.1 (2021): 1-19. **[Springer, IF:2.96, SCI]**
4. Kalyan Das, Satyabrat Das, and **Sibarama Panigrahi***, "Energy-Efficient Forecasting of Temperature Data in Sensor Cloud System Using a Hybrid SVM-ANN Method." Wireless Personal Communications, 129 (4) (2023), 2929-2944. **[Springer, IF:2.01, SCI]**
5. Sourav Kumar Purohit, **Sibarama Panigrahi***, Prabira Kumar Sethy, and Santi Kumari Behera. "Time series forecasting of price of agricultural products using hybrid methods." Applied Artificial Intelligence (2021), vol. 35, no. 15, pp. 1388-1406. **[Taylor & Francis, IF:2.78, SCI]**
6. S. S. Pradhan, **Sibarama Panigrahi***, S. K. Purohit, and J. Dash. “Study and development of hybrid and ensemble forecasting models for air quality index forecasting.” Expert Syatems (2023). **[Wiley, IF: 3.3, SCI]**
7. Sourav Kumar Purohit, and **Sibarama Panigrahi***. "Novel Deterministic and Probabilistic Forecasting Methods for Crude Oil Price employing Optimized Deep Learning, Statistical and Hybrid Models." *Information Sciences*, vol. 658, 120021 (2024). **[Elsevier, IF:8.1, SCI]**

RELATED PUBLICATIONS[FUZZY TIME SERIES FORECASTING]

1. **Sibarama Panigrahi**, and Himansu Sekhar Behera. "A study on leading machine learning techniques for high order fuzzy time series forecasting." Engineering Applications of Artificial Intelligence 87 (2020): 103245. **[Elsevier, IF: 7.80, SCI]**
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5. Radha Mohan Pattanayak, Himansu Sekhar Behera, and **Sibarama Panigrahi**. "A Novel High Order Hesitant Fuzzy Time Series Forecasting by using mean Aggregated Membership value with Support Vector Machine." Information Sciences (2023). **[Elsevier, IF: 8.01, SCI]**
6. Sushree Subhaprada Pradhan, **Sibarama Panigrahi***, “A study and development of high-order fuzzy time series forecasting methods for air quality index forecasting”. Journal of Forecasting (2024). **[Wiley, IF:3.4, SCI]**

Related Projects

#	Project Title	Sponsoring Agency	Scheme	Investigators	Amount	Duration
1	Studies on Deep Learning Models for Crude Oil Price Forecasting	SERB, Government of India	Core Research Grant	**PI: Dr. Sibarama Panigrahi Co-PI: NIL**	22.077 Lakhs	2022-2025
2	Design and Development of Large Scale Time Series Forecasting Methods using Deep Learning Techniques	Odisha State Higher Education Council, Government of Odisha.	OURIIP-2020	**PI: Dr. Sibarama Panigrahi Co-PI: NIL**	4.5 Lakhs	2021-2023

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