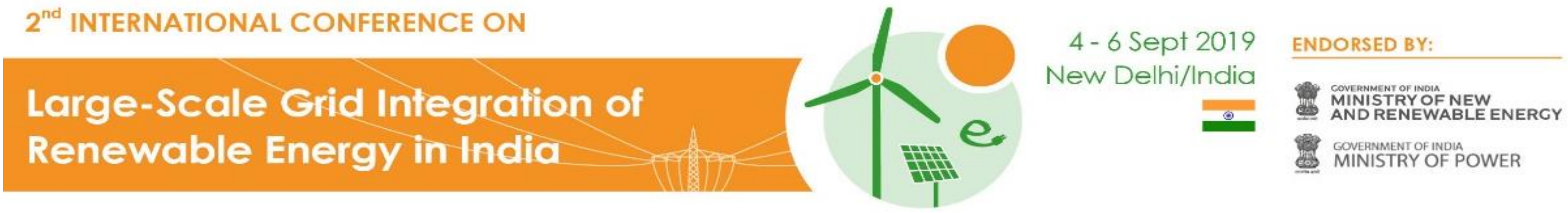
A COMPARATIVE STUDY OF SHORT-TERM WIND SPEED FORECASTING MODELS (SUBMISSION ID- 098)



PRESENTED BY:

ARCHITA VIJAYVARGIA

CO-AUTHORS:

DR. ROHIT BHAKAR
DR. KAILASH CHAND SHARMA

OUTLINE:

- Introduction
- Motivation
- Time series model
- Machine learning models
- Case study and Results
- Conclusions and Future scope
- References

INTRODUCTION:

Increasing demand for energy and global warming issues require-

- Clean and less carbon emission generation resources.
- Reconciled consistently increasing demand for energy.
- Projected by CEA that between 2017-22, the electrical energy requirement will grow by 5.51 percent cumulatively.

USE RENEWABLE GENERATION

SOLAR **WIND** BIOMASS SMALL HYDRO GEOTHERMAL

Load Generation Balance Report, 2018-19 [online]

MOTIVATION:

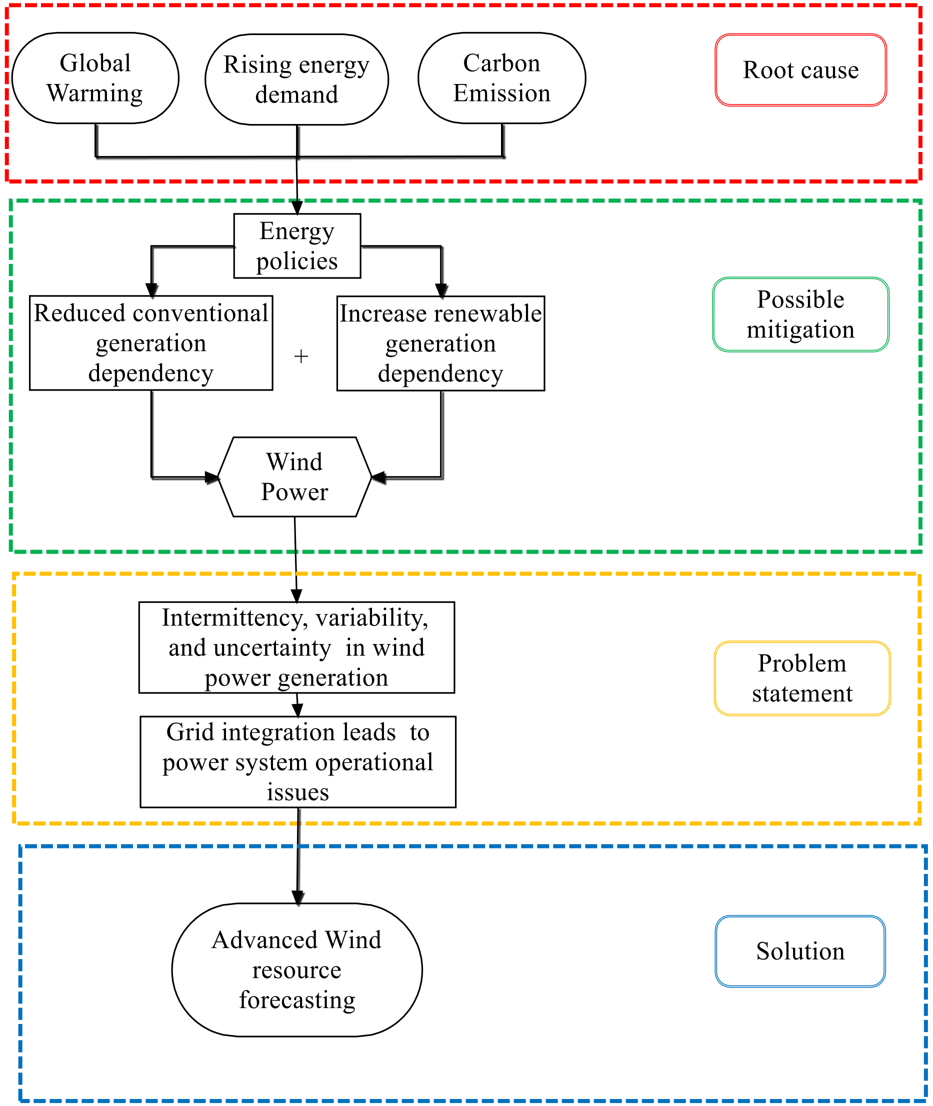


Fig. 1. Wind power grid integration.

Zaccheus O., et al., 2012,
Wang X., et al., 2011,
Chang W., 2014

ADVANTAGES OF WIND RESOURCE FORECASTING:

Some of the **advantages of accurate wind resource forecasting** and its adequate integration into powers system are:

REDUCES

- The need for additional balancing power.
- The need for reserve and ancillary services.
- Financial and technical risk of uncertainty of wind power production.

ENABLES

- Better dispatch and UC of thermal generators.
- Better stability and reliability.
- More competitive market trading.

Temitope R.A., et al., 2012, Wang X., et al., 2011

CLASSIFICATION OF WPF/WSF :

Very Short-term forecasting
Short-term forecasting
Medium-term forecasting
Long-term forecasting

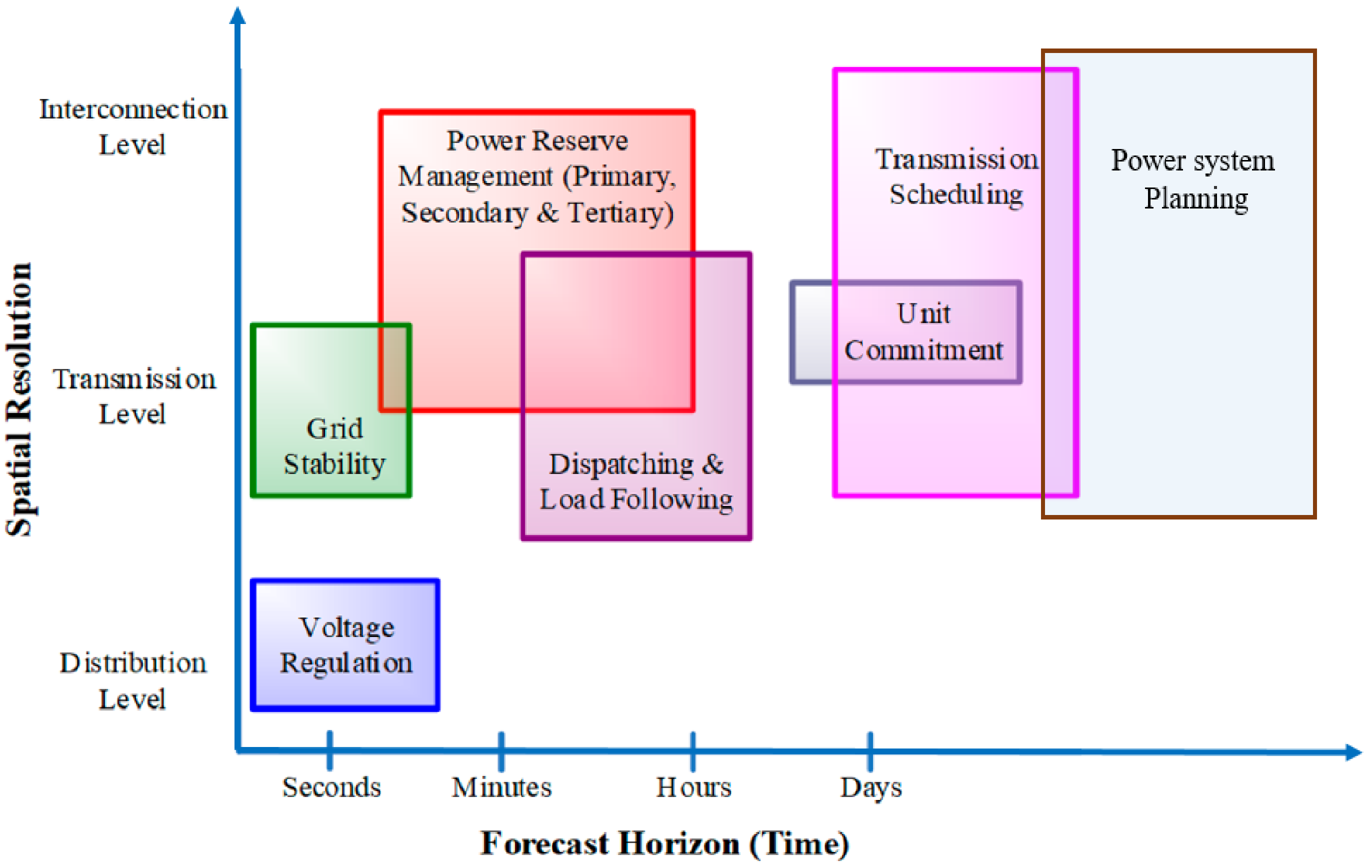


Fig. 2. Distribution of power system applications with forecast horizon and spatial resolution.

Lei M., et al., 2009, Soman S.S., et al., 2010, Wang X., et al., 2011

WIND FORECASTING MODELS:

WIND FORECASTING MODELS

- **Physical Models**
  - **NWP**
    - Orography, Obstacles, Terrains, Temperature, etc.
- **Statistical Models**
  - **Time series, ARIMA**
    - Historical time series data
- **Machine Learning models**
  - **ANN, linear regression, k-NN, etc.**
    - Historical data for learning purposes

Wang X., et al., 2011, Lei M., et al., 2009, Bhaskar M., et al., 2010

TIME SERIES MODELS MATHEMATICAL FORMULATION:

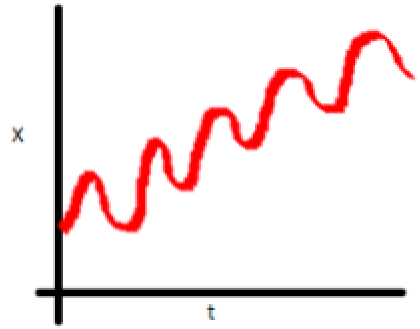
Mathematical Transformations for Stationarity:

$$y'_t = y_t - y_{t-1}$$
$$y_t^{\ln} = \ln(y_t)$$

ARIMA Model:

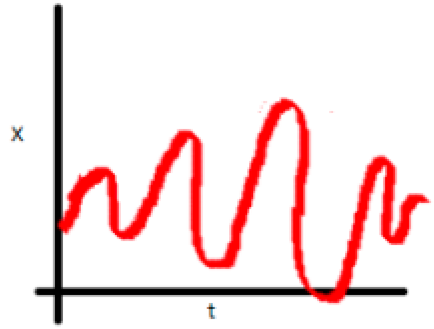
$$y_t^d = c + e_t + \sum_{k=1}^{p} \phi_k y_{t-k}^d + \sum_{j=1}^{q} \theta_j e_{t-j}$$

(a.)



$$ACF = \frac{\frac{1}{(n-k)} \sum_{t=k+1}^{n} (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sqrt{\frac{1}{n} \left(\sum_{t=1}^{n} (y_t - \bar{y})\right) \frac{1}{(n-k)} \sum_{t=k+1}^{n} (y_{t-k} - \bar{y})}}$$

(b.)



$$PACF = \frac{\mathrm{cov}(y_t, y_{t-k} | y_{t-1}, \dots, y_{t-k+1})}{\sqrt{\mathrm{var}(y_t | y_{t-1}, \dots, y_{t-k+1}).\, \mathrm{var}(y_{t-k} | y_{t-1}, \dots, y_{t-k+1})}}$$

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

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

TIME SERIES UNIVARIATE ARIMA MODEL ALGORITHM

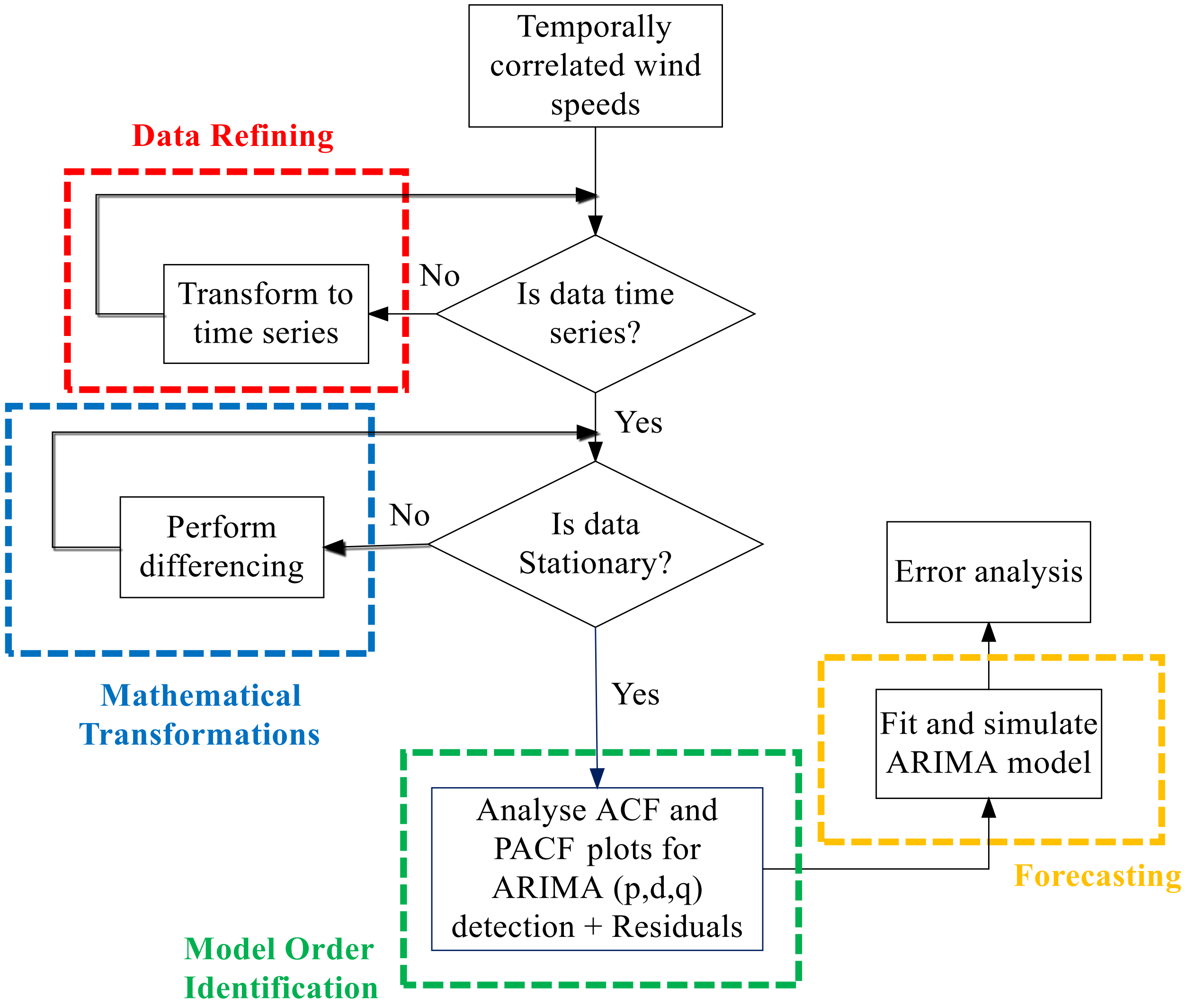


Fig. 3. Statistical ARIMA model algorithm developed in R-Studio.

MACHINE LEARNING ALGORITHMS:

MACHINE LEARNING

- **SUPERVISED LEARNING**
  - **LINEAR REGRESSION** → linear approach to model the relationship between a scalar response and one or more explanatory variable.
  - **k- NEAREST NEIGHBOURS** → ‘k’ specifies the number of neighbours to be considered.
- **UNSUPERVISED LEARNING**

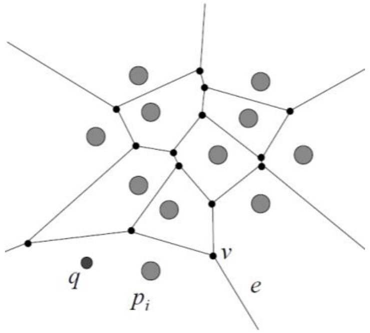


Fig. 4. Voronoi Tessellation for k-NN.

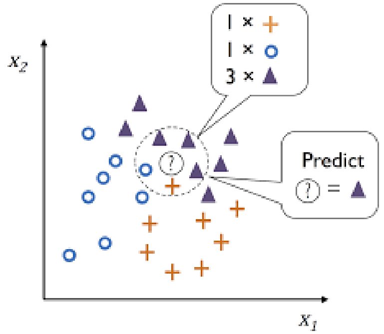


Fig. 5. k-NN decision making criteria.

Wang X., et al., 2011, Mitchell T.M., et al., 1997 [Online]

MACHINE LEARNING ALGORITHMS:

MACHINE LEARNING

SUPERVISED LEARNING

UNSUPERVISED LEARNING

ARTIFICIAL NEURAL NETWORK

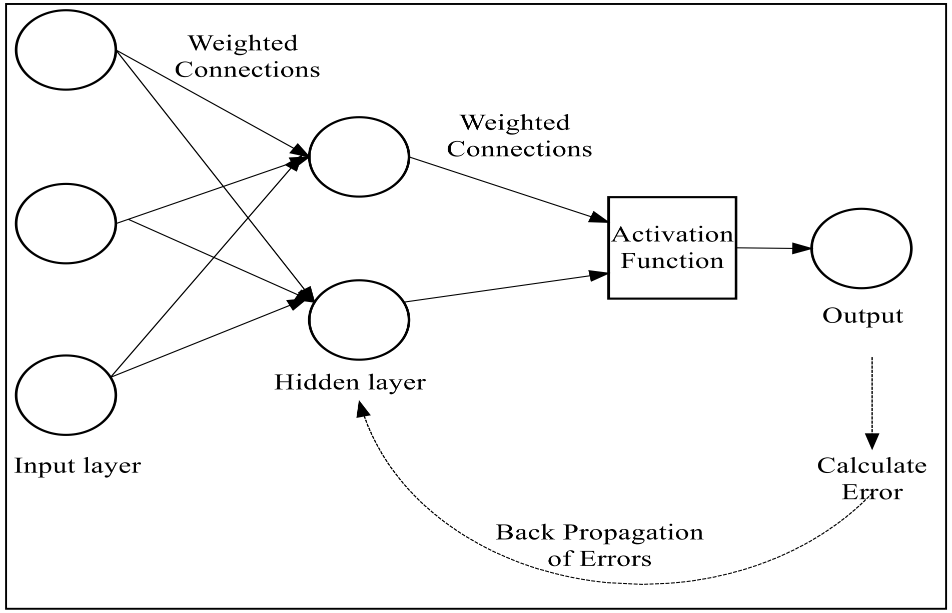


Fig. 6. Basic MLP based ANN layers.

Wang X., et al., 2011, Mitchell T.M., et al., 1997 [Online]

ANN MODEL MATHEMATICS:

Univariate ANN objective function: (minimize)

$$E(wt,\beta)=\sqrt{\frac{1}{h}\sum_{i=1}^{h}\left[y_i - f\left(x_i, wt, \beta\right)\right]^2}$$

For every new iteration:

$$wt \rightarrow wt + \Delta wt$$

$$\beta \rightarrow \beta + \Delta\beta$$

Compute optimized values of Δwt and $\Delta\beta$:

$$f(x_i, wt + \Delta wt, \beta + \Delta\beta) \approx f(x_i, wt, \beta) + G(\Delta wt + \Delta\beta)$$

wt= synaptic weights, β= bias, h= number of neurons in hidden layer

MACHINE LEARNING ALGORITHM:

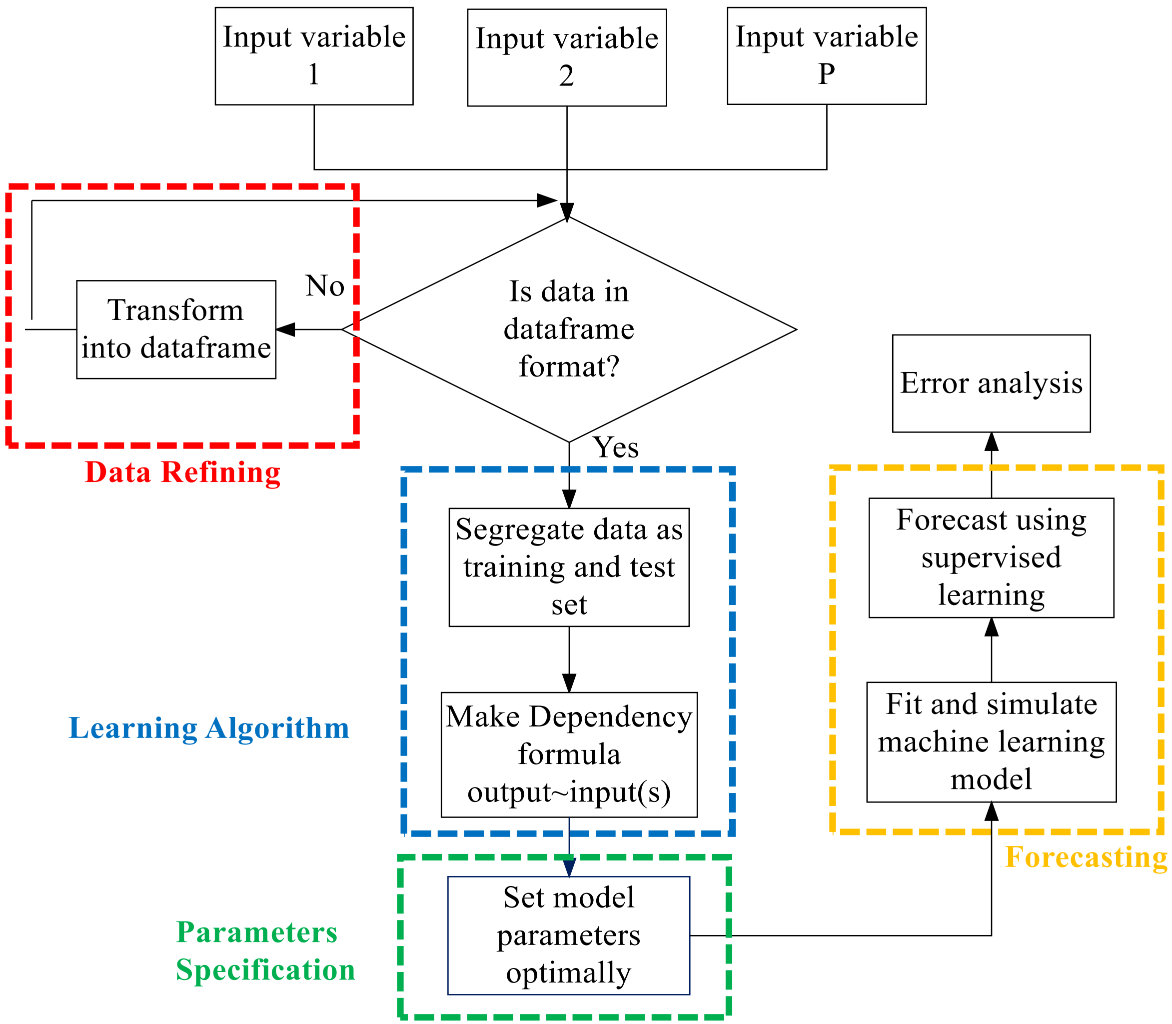


Fig. 7. Machine learning models (linear regression/ k-NN/ANN) algorithm developed in R-Studio.

CASE STUDY:

Dataset Source: NIWE, Chennai (open source-trial dataset).
Location: Jaisalmer wind farm, Rajasthan, India – September 2018 - recorded @10 minutes.

Physical Parameters – Hub height-120 meters,
Average wind speed-8.1166 m/sec

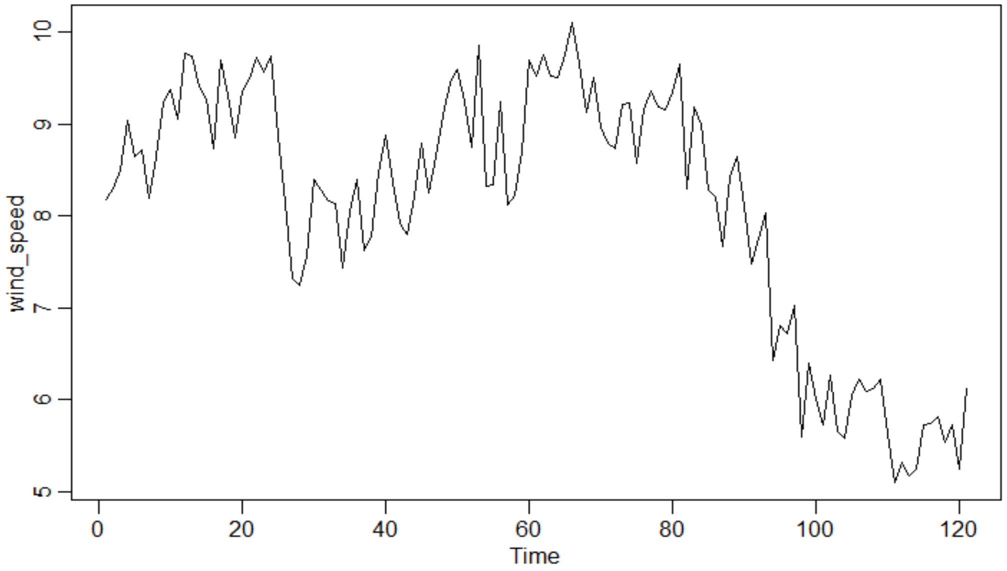


Fig. 8. Non-stationary time series wind speed data used for modelling the wind speed forecasting.

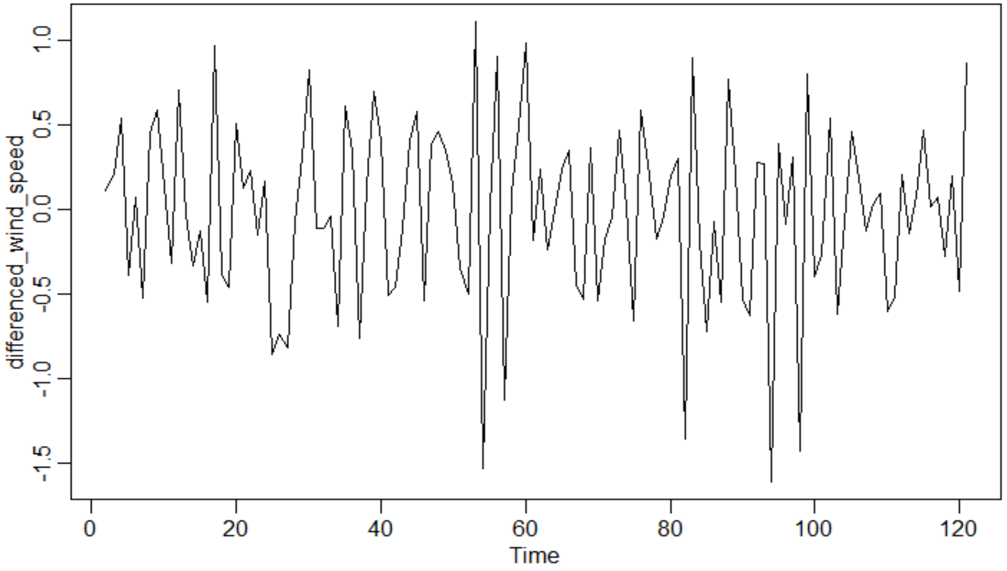


Fig. 9. Stationary differenced time series wind speed data used for modelling the wind speed forecasting.

GRAPHICAL RESULTS OF ARIMA:

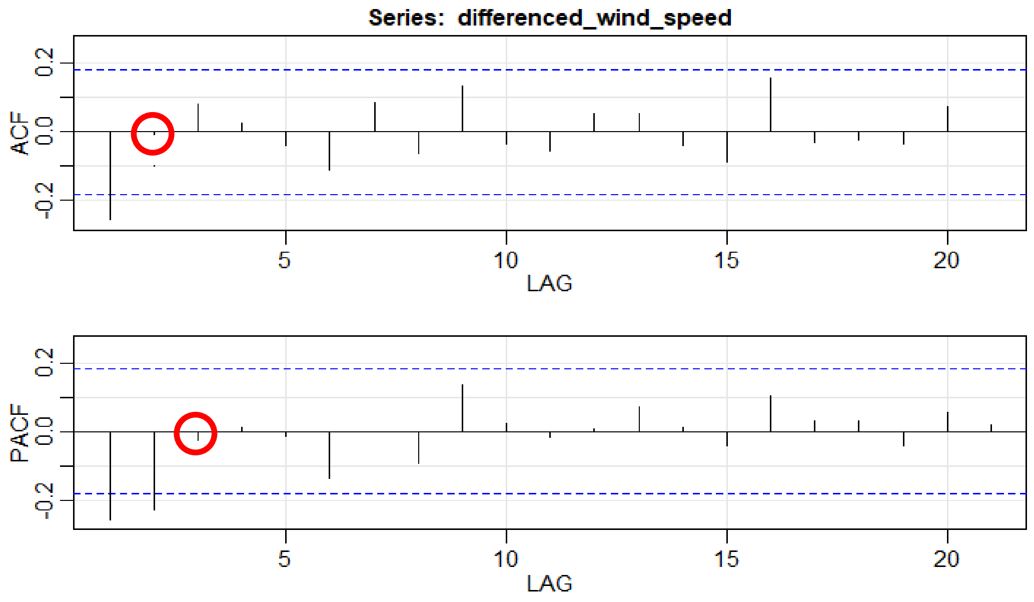


Fig. 10. ACF and PACF plots for differenced wind speed series.

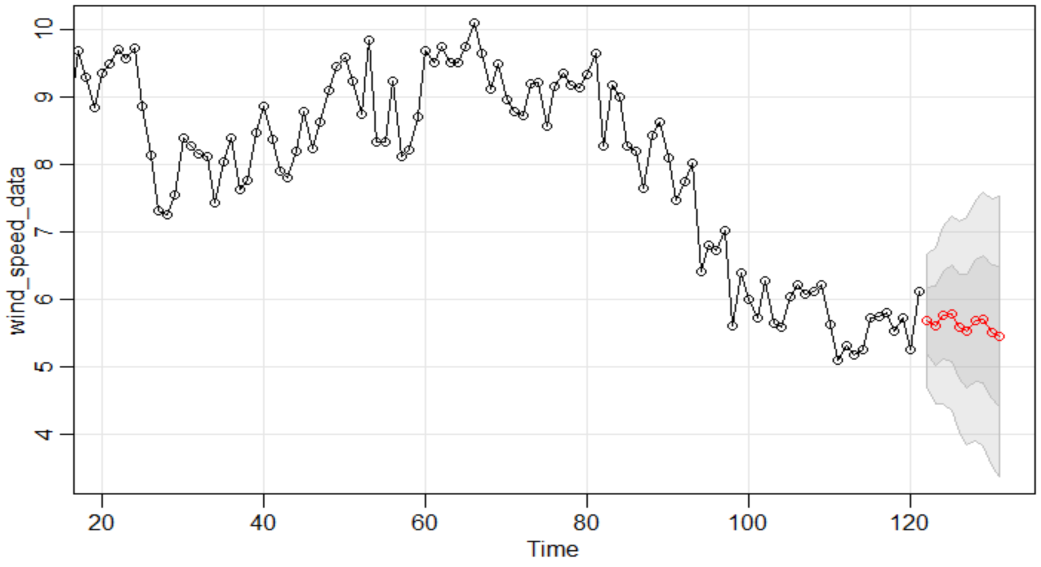


Fig. 11. Forecasts of wind speed obtained using ARIMA.

Graphical Results of k-NN and ANN

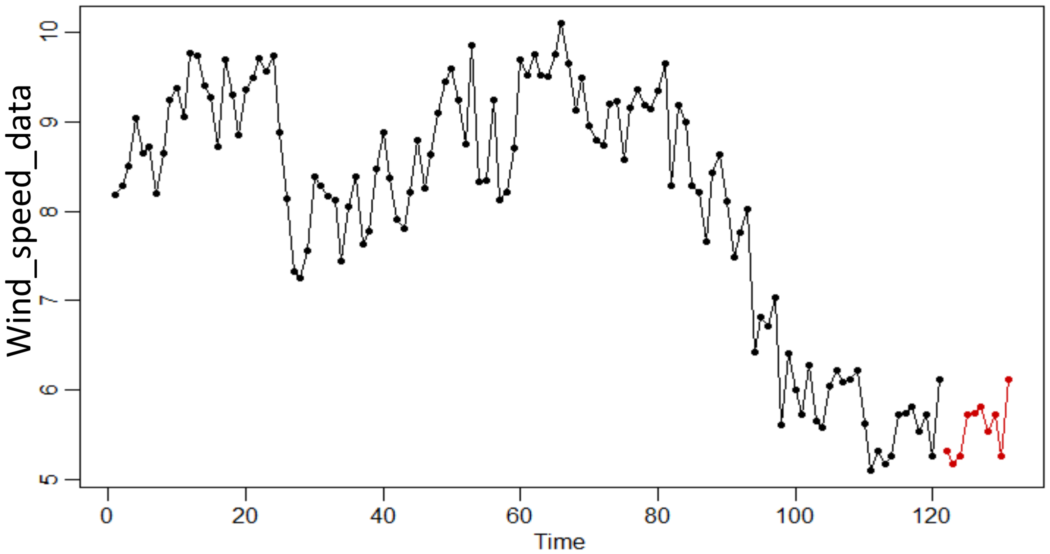


Fig. 12. Forecasts of wind speed obtained using k-NN.

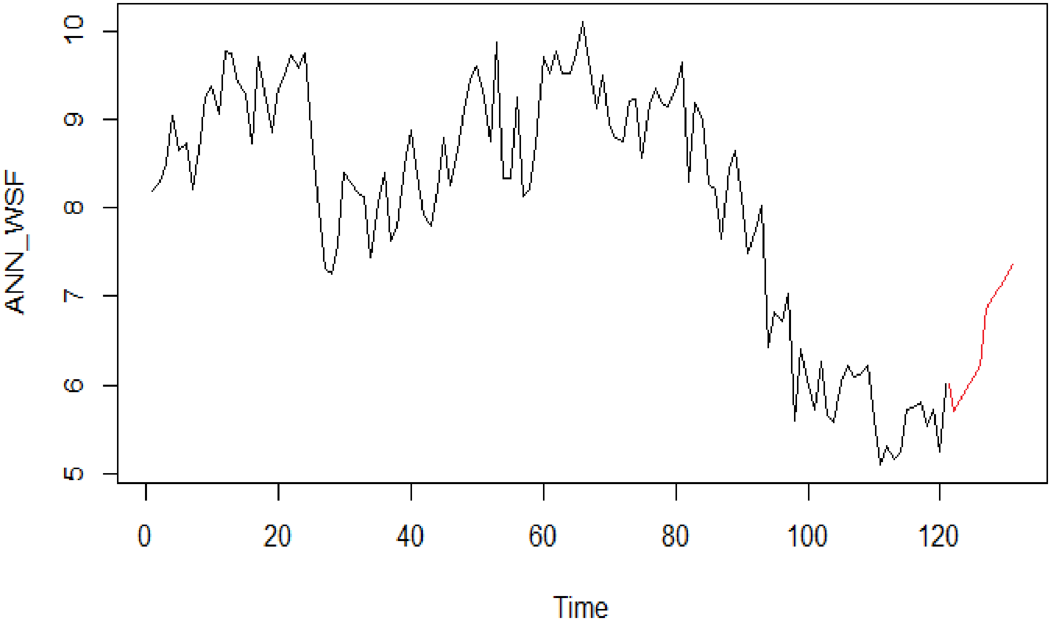


Fig. 13. Forecasts of wind speed obtained using ANN.

Table I

Comparative results of univariate ARIMA, linear regression, k-NN and ANN models

Actual Wind Speeds (m/sec)	Predicted Wind Speeds (m/sec)			
	ARIMA	LR	k-NN	ANN
6.12	5.94	6.51	5.31	5.703
6.43	5.73	6.494	5.17	5.831
5.93	5.84	6.479	5.25	5.959
6.26	5.73	6.463	5.72	6.087
5.44	5.778	6.447	5.74	6.215
5.69	5.712	6.369	5.81	6.856
6.48	5.724	6.354	5.53	6.984
6.47	5.681	6.338	5.73	7.112
7.1	5.676	6.322	5.25	7.24
7.57	5.64	6.307	6.12	7.36
RMSE	0.834	0.830	0.920	0.472
MAE	0.782	0.654	0.864	0.415

Order of forecast accuracy:

ANN > LR> ARIMA > *k*-NN

COMPARATIVE ANALYSIS:

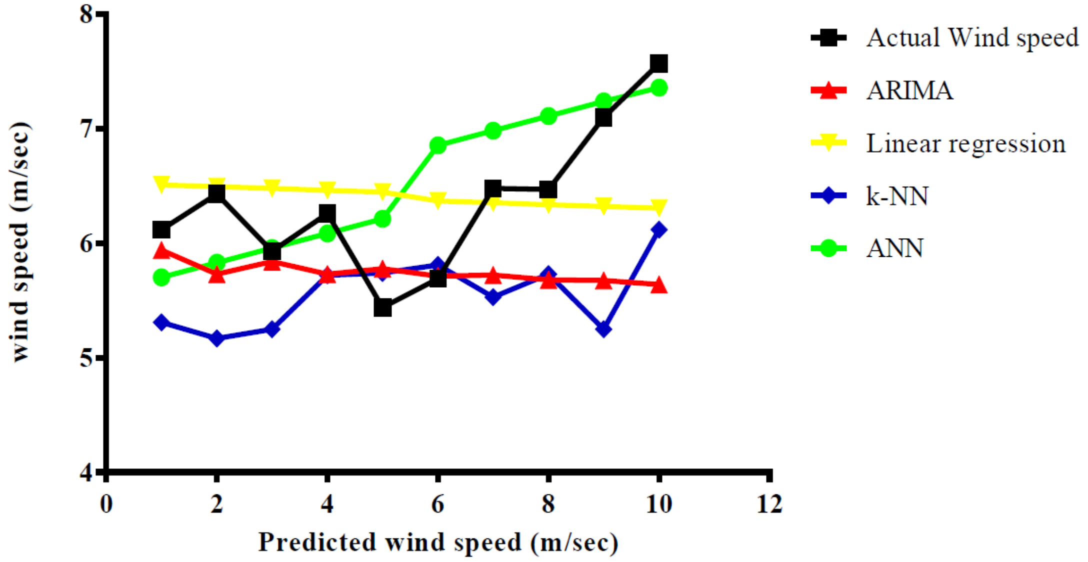


Fig. 14. WSF comparative analysis using ARIMA, LR, k-NN, and ANN.

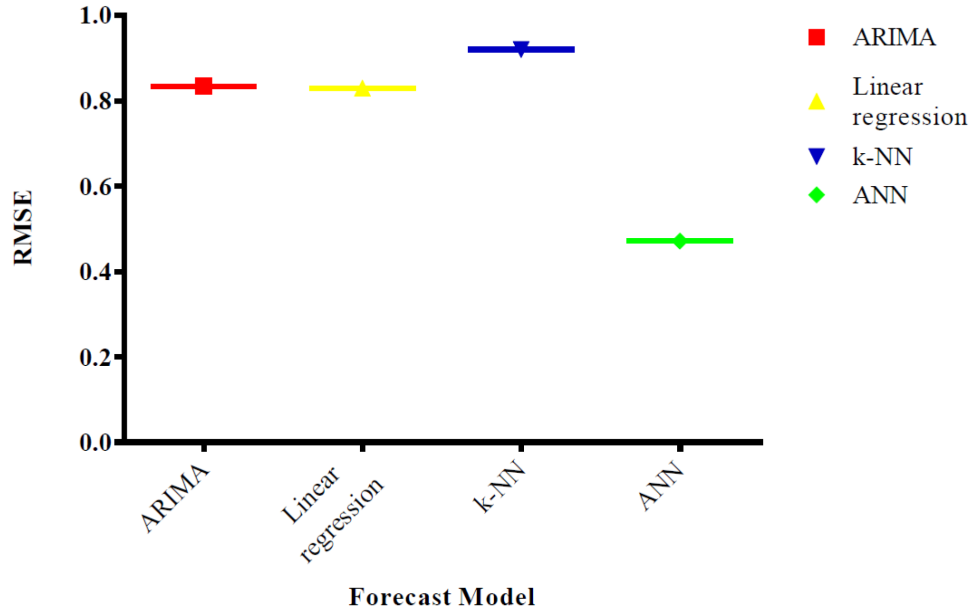


Fig. 15. RMSE comparison for ARIMA, LR, k -NN, and ANN.

CONCLUSIONS:

- Numerical results imply that machine learning based ANN has maximum forecast accuracy out of the four mentioned models.
- ANN fits the dataset best due to its enormous capacity to learn and predict.
- ARIMA model is not so accurate because the forecasts converge to the mean of the series after some forecast values. Similar is the case of LR.
- k-NN is having the least accuracy because it is more a classification approach rather than regression approach.

FUTURE SCOPE

- Propose an advanced WSF technique that considers the spatio-temporal dependency of WFs located near each other.
- Impact assessment of spatio-temporal correlations in wind forecasting.

REFERENCES:

1. M. I. Alizadeh, M. Parsa Moghaddam, N. Amjady, P. Siano, and M. K. Sheikh-El-Eslami, “Flexibility in future power systems with high renewable penetration: A review,” Renew. Sustain. Energy Rev., vol. 57, pp. 1186–1193, 2016.
2. J. Jung and R. P. Broadwater, “Current status and future advances for wind speed and power forecasting,” Renew. Sustain. Energy Rev., vol. 31, pp. 762–777, 2014.
3. A. M. Foley, P. G. Leahy, A. Marvuglia, and E. J. Mckeogh, “Current methods and advances in forecasting of wind power generation,” *Rene. Energy*, vol. 37, no. 1, pp. 1-8, Jan. 2012.
4. J. Yan, Y. Liu, S. Han, Y. Wang, and S. Feng, “Reviews on uncertainty analysis of wind power forecasting,” *Rene. and Sust. Energy Rev.*, vol. 52, pp. 1322-1330, Dec. 2015.
5. Y. Zhang, J. Wang, and X. Wang, “Review on probabilistic forecasting of wind power generation,” *Renew. and Sustain. Energy Rev.*, vol. 32, pp. 255-270, 2014.
6. M. H. Albadi and E. F. El-Saadany, “Overview of wind power intermittency impacts on power systems,” *Electric Power Syst. Res.*, vol. 80, no. 6, pp. 627–632, June 2010
7. D. B. Alencae, R. C. L. Oliveira, and J. L. M. Rodrigaz, “Different models for forecasting wind power generation: Case Study,” *Energies*, vol. 10, no. 1976, pp.1-27, 2017.
8. K. Yunus, T. Thiringer, and P. Chen. “ARIMA-based frequency-decomposed modeling of wind speed time series,” *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2546-2556, 2015.
9. S. Buhan, Y. Ozkazanc, and I. Cadirci, “Wind pattern recognition and reference wind mast data correlations with numerical weather prediction for improved wind-electric power forecasts,” *IEEE Trans. Ind. Informat.*, vol. 12, no. 3, pp. 991-1004, Jun. 2016.
10. S. Zhang, X. Li, M. Zhong, X. Zhu, “Effective knn classification with different numbers of nearest neighbors,” *IEEE Trans Neural Netw Learn Syst.*, vol. 29, no. 5, pp. 1774-1785, 2017.

THANK YOU