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Most influential parametrical and data needs for realistic wind speed prediction

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ABSTRACT

Depleting fossil fuel reserves and increasing global weather concerns has diverted mankind to look out for clean and green reserves of energy ever since the beginning of last decade. Wind holds a major role in satisfying our energy needs, however, its use as an alternate power source accounts for various issues such as deregulation of supply, frequency instability, etc. In order to nullify such effects, power engineers need to have an idea of futuristic weather conditions, especially the wind speed trend. Numerical Weather Prediction (NWP) tools such as Yearly Auto-Regressive (YAR) models when deployed for medium-term wind speed forecasting have proved their effectiveness. In this paper Artificial Neural Network based Yearly Auto-Regressive (ANNYAR) model have been used to figure out the most influential parameter's affecting wind prediction and corresponding range of yearly data set required for Time Horizon (TH) extending from 6 to 96 h. Data from area in and around 'VABB airfield Mumbai' has been incorporated for modelling and analysis purpose.

1. Introduction

Wind has always been considered as an alternate energy source ever since the evolution of mankind. It has often been deployed for a number of applications, such as grain grinding mills, driving ships, etc., in ancient period to fulfilling electricity and energy needs in the current era. Inspite of the fact that wind possesses tremendous power and abundance in nature, human race has not been able to grab this source efficiently with total installed wind farms being much lesser than 0.0001% of net wind power capacity available. Going by fixtures total wind power capacity stands at 336 GW with more than three hundred thousand wind turbine operating till June, 2014 [1]. Wind power is expected to rise through 200 GW in the current fiscal year with a market penetration of 3.85% [2,3]. China holds the tag for maximum cumulative wind capacity installation of 114.76 GW (31.1% of world) followed by United States (65.9 GW (17.8%)) and Germany (39.2 GW (10.6%)). India holds 5th position in wind penetration with a total nameplate capacity of 22.5 GW (6.1%) [4].

It's a global certitude that wind farm output is a cubic function of instantaneous/average wind speed at the target site which varies instantaneously in a matter of seconds. Inspite of all prominent features wind power integration into on-grid or off-grid systems leads to numerous power issues such as voltage variations, steady state and transient state stability conditions, harmonics, frequency and power control problems, reactive power compensation complications, etc., [5]. In order to counteract these problems power engineers need to have a clear impression of the complexity of problem that could stand up in the near future. Wind speed prediction techniques enables power system engineers to analyze futuristic condition and develop systems accordingly. Wind speed forecasting could be used for purposes such as controlling grid dynamics, unit maintenance, control purpose, etc., in case of short-time horizon forecasting to purposes such as maintenance planning and determining feasibility of esteemed wind power projects in case of medium-term and long-term forecasting, respectively [6,7]. Medium-term forecasting models are the most complex systems which tend to depict seasonal, daily and hourly changes in futuristic weather conditions.

Stochastic techniques such as PCF, AR model, MA model, ARMA model, ARIMA model, VR method, Mortimer's method, MCP, WTT, ANN, etc., have already been incorporated for wind speed

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List of symbols

NWP	Numerical Weather Prediction
YAR	Yearly Auto-Regressive
ANNYAR	Artificial Neural Network based Yearly Auto-Regressive
TH	Time Horizon
PCF	Polynomial Curve Fitting
AR	Auto-Regressive
MA	Moving Average
ARMA	Auto-Regressive Moving Average
ARIMA	Auto-Regressive Integrated Moving Average
VR	Variance Ratio
MCP	Markov's Chain Process
WTT	Wavelet Transform Technique
ANN	Artificial Neural Network
SVM	Support Vector Machine
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error
COC	Coefficient of Correlation
PC	Parametrical Combination
MLP	Multi-layer Perceptron
LMBA	Levenberg–Marquardt Backpropagation Algorithm
MSE	Mean Square Error
DS	Data sample
PEP	Performance Evaluation Parameter
MAE	Mean Absolute Error

List of symbols

$Model_N$	Size of past yearly data set chosen for prediction
x_i, y_i	Set of I/P − O/P parameters fed to MLP neural network
wt	Weightage of input connection of ANN algorithm
β	Startup ANN correlation coefficient value
h	Number of hidden neurons in each layer
δ_{wt}, δ_{β}	Represents substantial change in value of wt and β
J_i	Gradient of I/P − O/P correlation function, f w.r.t wt and β
J	Jacobian matrix whose i^{th} row equals J_i
f	Corresponding vector whose i^{th} component is $f(x_i, \beta)$
y	Corresponding vector whose i^{th} component is y_i
λ	Non-negative damping coefficient
AR (N)	N^{th} order AR model
W^*_{i+1}	Predicted wind speed
W_{i-j+1}	Wind speed j^{th} times prior to W_{i+1}
a_j	Lag j AR correlation coefficient
a_o	Assumed random variable set as per wind trend
D	Numbet of data points considered for prediction purposes in single turn
W	Wind velocity
HR	Time of day
T	Air temperature
DW	Dew point temperature
H	Humidity
P	Barometric pressure
x	starting location of each series
$W^*_{N+1}(x+I)$	Predicted wind speed for current year
$HR_{(N+1)-j}(x+I)$, $W_{(N+1)-j}(x+I)$, $T_{(N+1)-j}(x+I)$, $DP_{(N+1)-j}(x+I)$, $H_{(N+1)-j}(x+I)$, $P_{(N+1)-j}(x+I)$	$((N+1)-j)^{th}$ year data series of NWP parameters constituting of D data points each with a step I (where, I ε 1, 2,…..D)
$b_1 - b_6$	PC selector coefficients (where, b ε 0,1)
$a_{1j} - a_{6j}$	Lag j correlation coefficients for NWP parameters
S_1	Winter sample used for analysis purpose
S_2	Summer sample used for analysis purpose
X_N	Normalized value of original data X
X_{min}	Minimum value of data series under consideration
X_{max}	Maximum value of data series under consideration
a	Minimum value of normalized data series (= 0)
b	Maximum value of normalized data series (= 1)
L	Number of input hidden layers selected for prediction
L_{opt}	Optimum value of L selected for best prediction results
CY	Current year, i.e., year for which predictions are made
Z	Total number of wind speed data points
$W_{N+1,i}$	Actual wind speed for current year at instant i
$W^*_{N+1,i}$	Predicted wind speed for current year at instant i
$R_{W_{N+1}W^*_{N+1}}$	Co-variance between W_{N+1} and W^*_{N+1}
$S.D.(W_{N+1})$	Standard deviation for W_{N+1}
$S.D.(W^*_{N+1})$	Standard deviation for W^*_{N+1}
$MAE_{(MEAN-HL)}$, $MSE_{(MEAN-HL)}$, $COC_{(MEAN-HL)}$	Average value of PEP calculated for hidden layer analysis
$MAE_{(MEAN-PN)}$, $MSE_{(MEAN-PN)}$, $COC_{(MEAN-PN)}$	Value of corresponding PEP obtained while forecasting for a given current year using pre-defined TH, yearly model $Model_N$ and PC (calculated while determining the optimum parametrical needs for best wind speed prediction)
$MAE_{(MEAN-DR)}$, $MSE_{(MEAN-DR)}$, $COC_{(MEAN-DR)}$	Value of corresponding PEP obtained while forecasting for a given current year using pre-defined TH, yearly model $Model_N$ and PC (calculated while determining the optimum data requirements for best wind speed prediction)
N_{CY}	Number of CY's selected for prediction (here, $N_{CY} = 5$)
PC_{opt}	Most influential parameters selected for best prediction results
$Model_{N(opt)}$	Optimum size of past yearly data set chosen for best prediction results

predictions ranging from instantaneous to long-term time horizons [8–22]. Hybrid models involving ARMA-ANN, ARIMA-ANN, ARMA-WTT, etc., have been analyzed for short-cum-medium term prediction [23,24]. For short-term predictions purposes linear auto-regressive models seems to be quite a bit impressive due to its easy implementation and lesser technical complexity. Lei et al. suggested one such method wherein predictions are made by firstly decomposing original wind speed pattern into a number of low frequency components and then going for forecast analysis of each decomposed signal using ARMA model. It resulted in 50.0% and 35.2% improved results over persistence and ARMA model, respectively [23]. Wavelet approach is good as it aims to track each frequency signal individually, instead of tracking source wave shape as a whole. Low frequency could be tracked quite brilliantly with minimum error in comparison to high frequency components [16,17], [23,24]. Patil et al. deployed SVM for 24 h ahead prediction