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Enactment of Conventional Machine Learning Algorithms for Predicting CFBC Cyclone Separator Performance

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ABSTRACT

Machine Learning is one of the latest evolving technologies. During the boiler design stage, the selection of a suitable cyclone separator for CFBC boiler is very crucial. In this study, an attempt is made to apply machine learning algorithms to predict cyclone separator output used for CFBC boilers. Dynamic analysis of computational fluid is carried out for cyclone separators by varying velocity of inlet. For selected machine learning algorithms such as K-Nearest Neighbours, Neural Network, Linear Regression, Support Vector Machine, Support Vector Machine Evolutionary, Deep Learning, Polynomial Regression, and Gaussian Method, the data set generated in CFD analysis is used as a training dataset. These models are compared statistically with predicting the pressure drop and the efficiency of separation. Neural Network is proven statistically best and applied to all models of cyclone separators, both pressure drop and separation efficiency are expected and compared with CFD analysis. The consequence of this comparison is that Neural Network predicts perfectly a decrease in pressure for cyclone separator with a ratio of vortex finder diameter to cyclone separator diameter greater than 0.5. Likewise, Neural Network predicts cyclone separator separation efficiency with a ratio of cylinder height to cyclone separator diameter less than 2.

Key words: Machine Learning, Artificial Intelligence, Cyclone Separator, Pressure Drop, Separation Efficiency

1. INTRODUCTION

Circulating Fluidized Bed Combustion (CFBC) boilers have been used since the last two decades in many of India's thermal power plants. CFBC boilers are preferred to conventional boilers because of their reduced emissions of toxic substances such as Sox, Nox etc. This reduction in emissions results from reduced bed temperatures as low as 800-900 C [1]. CFBC boilers have two distinct multiphase flows, one draught down and other is draught up. Cyclone separator, located at the intersection of both down and up draught, serves as one of CFBC boiler's critical integral component [2]. Cyclone separator separates two distinct phases on the basic concept of centrifugal force supported by density difference between those two phases. When in action two issues are faced by cyclone separator, one is wearing refractory materials in the walls of separator and another reduction of pressure across the separator [3]. Refractory materials may be patched, but at the design level itself, pressure drop needs to be dramatically reduced [4]. Similarly, performance of cyclone separator is estimated by a parameter termed as separation efficiency [5]. This separation efficiency is to be calculated and can be increased during the design stage. Separation efficiency plays a vital role in selection of cyclone separator for CFBC boiler. Thus, prediction of these two parameters will aid the design engineer to select the proper cyclone separator for CFBC boiler.

Machine Learning (ML) is the one of the emerging technologies in Artificial Intelligence (AI). Many number of machine learning algorithms (MLAs) are available, these algorithms are just an iterative method of applying mathematical formulae's [6]. MLAs are classified into four different types as: unsupervised learning, supervised learning, semi-supervised learning and reinforced learning [7]. Unsupervised learning technique is applied to MLAs when training dataset is not available for the study to identify the hidden pattern of data [8]. Supervised learning technique is utilized in MLAs when there is specific training dataset is available to predict the data patterns [9]. Semi-supervised learning is similar to supervised learning except some data are missing in training dataset [10, 11]. Rein-forced learning technique is employed to MLAs whenever an external feedback given to analyze the data pattern [12, 13].

Until now cyclone separator performance parameters are estimated with the help of CFD analysis [14]. If the turbulence model is not properly selected then the results may vary and by selecting correct model it may take even 4 to 5 hours to complete a single CFD analysis [15]. Thus, CFD analysis for every variation of performance is a time-consuming process. MLAs are time effective for prediction of performance parameters. Hence, this work is to supervised learning technique is implemented to various traditional MLAs to predict performance parameters of cyclone separator and compare be-tween these algorithms to provide a single algorithm for perfect prediction.

2. DESIGN & ANALYSIS OF CYCLONE SEPARATOR

2.1 Design Approach

Six different separators are availed in the past for CFBC boilers. These six separators are designed with the aid of Table 1 and with following procedure

- Fix the volume flow rate (Q) that must be handled by cyclone separator, in this study volume flow rate is taken as 500 m^3/hr [16]
- Cyclone separator inlet duct area is to be estimated with equation (1) by considering the operating velocity. In general, CFBC boilers operates with velocity ranging from 15m/s to 30 m/s[17]. For this study operating velocity of cyclone separator is considered as 15m/s

$$Q = A_{in} \times v_{in} \qquad -(1)$$

$$A_{in} = D \times B \qquad -(2)$$

Table 1: Relationship between the dimensions of various cyclone separators with their respective diameters[18]

S.No	Types of Cyclone Separator	$\frac{D}{D_{cy}}$	$\frac{B}{D_{cy}}$	$\frac{D_v}{D_{cy}}$	$\frac{H_v}{D_{cy}}$	$\frac{S}{D_{cy}}$	$\frac{H}{D_{cy}}$	$\frac{E}{D_{cy}}$
1.	Stairmand High Throughput (HT)	0.75	0.375	0.75	0.875	1.5	4.0	0.375
2.	Swift High Throughput (HT)	0.8	0.35	0.75	0.85	1.7	3.7	0.4
3.	Swift General Purpose (GP)	0.5	0.25	0.5	0.6	1.75	3.75	0.4
4.	Lapple General Purpose (GP)	0.5	0.25	0.5	0.625	2.0	4.0	0.25
5.	Swift High Efficiency (HE)	0.44	0.21	0.4	0.5	1.4	3.9	0.4
6.	Stairmand High Efficiency (HE)	0.5	0.22	0.5	0.5	1.5	4.0	0.375

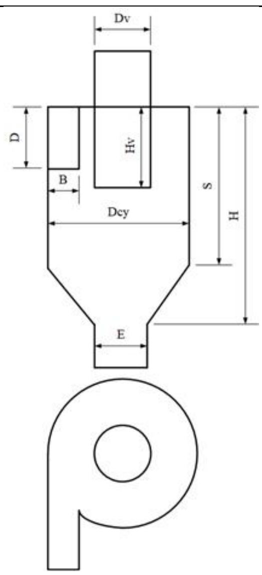

Figure 1: Cyclone Separator Design Parameters[18]

- Convert inlet area into diameter of cyclone separator (D_{cy})using equation (2) and table 1 [18].
- Using diameter of cyclone separator (D_{cy}) calculate other parameters of cyclone separator as shown in Figure 1 using Table 1.
- Virtual model of all six-cyclone separator is developed with a design software SOLIDWORKS 2016 [3] as shown in Figure 2

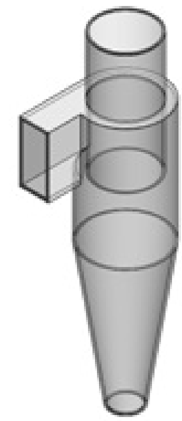

Figure 2: Virtual Model of Swift HT cyclone separator developed in SOLIDWORKS 2016

2.2 Analysis Approach

Two main Performance parameters of cyclone separator are separation efficiency and pressure drop. These parameters are estimated by eqn (3) & (4) after performing CFD analysis in a simulation software Ansys fluent 18.1. To perform analysis virtual model created in SOLIDWORKS 2016 is exported to Ansys fluent. Imported model is broke into tiny areas of study is termed as mesh grid. Three types of mesh grid are available in fluent as: coarse, intermediate and fine.

$$\Delta P = P_{out} - Pin \qquad -(3)$$

$$-(4)$$

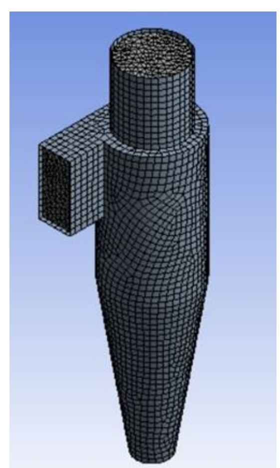

Figure 3: Coarse square mesh grid of Swift HT model cyclone separator

Many researchers employ fine grid because of the uncertainty of simulation study[19]. But according to Lewis Fry Richardson if refinement ratio is higher than 1.3 then that type of grid is acceptable for performing CFD study[20]. In our study coarse mesh is having a refinement ratio as 1.357, hence coarse grid is applied to all six models of cyclone separator and a sample is shown in Figure 3. Type of flow should be selected for CFD study, since cyclone separator handles two distinct phases multiphase flow to be selected [21]and further some of the assumptions to be considered as, incompressible unsteady turbulent flow with no heat loss to the surroundings[22]. Reynolds-average continuity and Navier-Stokes (RANS) equation is employed in fluent for incompressible turbulent flow [23]and Euler-Lagrangian approach is utilized for multiphase flow[24].

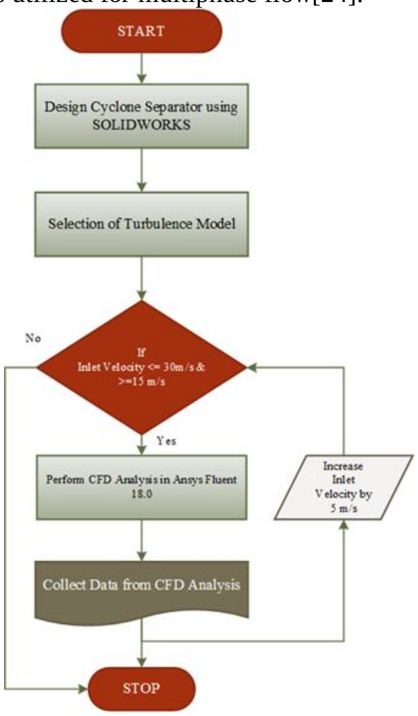

Figure 4:. Process Flowchart for Designing and CFD Analysis of Cyclone Separator

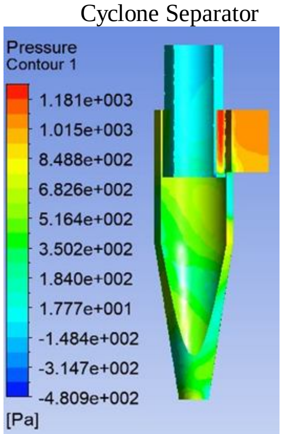

Figure 5: Pressure contour of Swift HT model cyclone separator

Since the flow in cyclone separator is turbulent a turbulent model to be selected for performing CFD analysis. Previous studies depicts that Reynolds Stress Model (RSM) is most suited for swirl flow occurring in cyclone separator[25, 26]. Thus, RSM turbulent model is preferred for this simulation study. CFD study is performed for all six models of cyclone separator by varying the inlet velocity from15 m/s to 30 m/s with a step increase of 5 m/s as shown in Figure 4. Pressure contour and Turbulence Intensity contour are extracted from the study to estimate pressure drop and separation efficiency, sample contours are shown in Figure 5 &Figure 6.

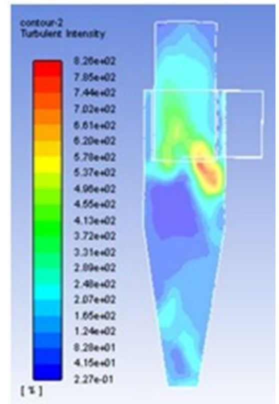

Figure 6: Turbulence Intensity contour of Swift HT model cyclone separator

Since the flow in cyclone separator is turbulent a turbulent model to be selected for performing CFD analysis. Previous studies depicts that Reynolds Stress Model (RSM) is most suited for swirl flow occurring in cyclone separator[25, 26]. Thus, RSM turbulent model is preferred for this simulation study. CFD study is performed for all six models of cyclone separator by varying the inlet velocity from15 m/s to 30 m/s with a step increase of 5 m/s as shown in Figure 4. Pressure contour and Turbulence Intensity contour are extracted from the study to estimate pressure drop and separation efficiency, sample contours are shown in Figure 5 &Figure 6.

3. MACHINE LEARNING ALGORITHM

Supervised learning is applied in number of research areas where numerous datasets are available for classify compare and predict[7, 27-29]. Supervised Learning is to be performed for the existing dataset for all six cyclone separator models to predict the intermediate dataset by using conventional MLAs. Some of the traditional MLAs available are as: K-Nearest Neighbour(KNN), Neural Net (NN)or Artificial Neural Network(ANN), Deep Learning(DL), Linear Regression(LR), Polynomial Regression(PR), Support Vector Machine(SVM), Support Vector Machine Evolutionary(SVM EVO), Gaussian Process (GP)[30]. Each of the MLAs has its own advantages and disadvantages in prediction all depends upon the type of dataset is employed for training MLAs.

K-nearest neighbours (KNN) are used as classifier algorithm for classifying unstructured dataset and considered as one of the laziest algorithm[31]. Further it can be used for obtaining missing values and regression analysis[32]. Hence in this case interpolation is performed for predicting missing values KNN is considered for the study.

Neural Net (NN) can perform both regression and classification in same network and obtain single output[33, 34]. This output depends on three basic aspects, first one is input to NN and activation functions, second is the network architecture and the last is weight of each connection. In these three aspects, only third aspect is a variable. NN will train the network to the accuracy by changing the weights[35]. If the relation between independent and dependent are nonlinear in nature then Neural Network is an effective method of prediction[36]. Hence this MLA is selected for prediction analysis of cyclone separator performance. Deep Learning (DL)algorithms is a subset of machine learning, mainly used for dealing large amount of unstructured data for processing[37]. It works similar to human brain and have high accuracy in prediction data when compared to other MLAs such as logistic regression and support vector machine (SVM)[38]. Hence DL can be employed for this study.

Linear Regression (LR) algorithms are one of the oldest methods of fitting the dataset into a line linear in nature. LR utilises method of least square to form a linear relation between independent and dependent variables[39]. If the number of population in a sample size is less than 20 then linear regression is an effective method of prediction[40]. When the relation between independent and dependent variables are not linear then polynomial regression (PR) algorithms can be employed. Since in this case the relationship between the variables is unknown hence both MLAs are selected for the study.

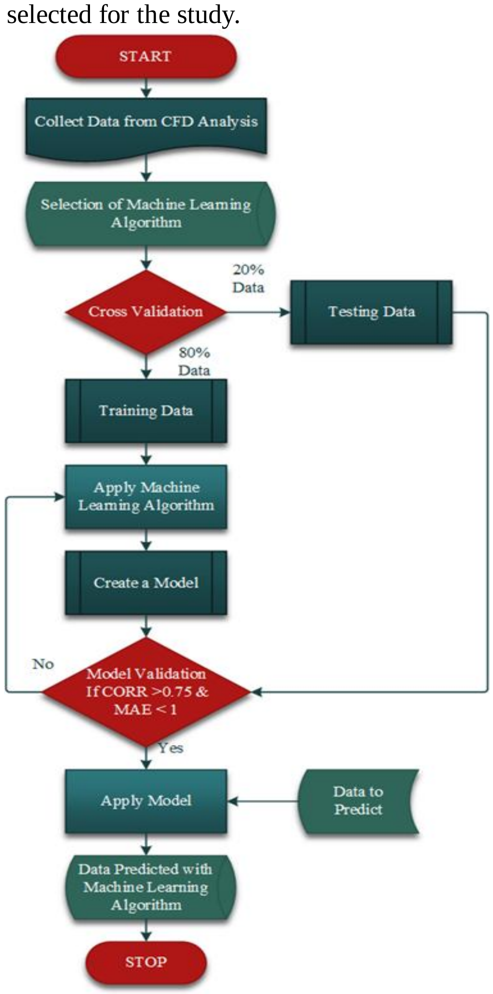

Figure 7: Process Flowchart for Applying Machine Learning Algorithm to Predict Data

Support Vector Machine (SVM) evolved during the early 90's similar to NN, SVM can be applied for both classification and regression[41]. SVM classifies the data by employing the hyper plane and regression analysis is performed with maximum margin of hyper plane[42]. Support Vector Machine Evolutionary (SVM EVO) algorithm is generic than the standard SVM and utilizes negative semi-definite kernel functions for prediction. SVM EVO is an algorithm combination of evolutionary algorithm and particle swam optimization algorithm[43]. Since SVM is similar to NN and SVM EVO is a one step ahead of SVM both MLAs are employed for this predictive analysis.

Gaussian Process (GP) algorithm is an iterative method employed for both classification and regression process. Gaussian process regression model algorithm predictions are having better effective than other MLAs like SVM, Neural Networks[44], multiple regression and random forest[45].Hence GP algorithm is considered for this study.

A predictive analytics software Rapid miner studio v9.7.0 is used in this study to carry out the traditional MLAs' predictive analysis. Rapid miner studio's workflow is depicted in Figure 7, the data generated from Ansys Fluent's CFD analysis is given to the software as the input data. This database is randomly divided into 80 % and 20%. Those 80 percent data serve as a database for preparation and 20 percent data serve as a database for research. Throughout the training process, 10-fold cross validation is applied to draw the best prediction out of each MLAs. When the training process is completed, there is a testing phase in which the remaining 20 percent data is added to the produced predictive model. MLAs performance is validated with CORR and MAE, if both are within the limitations then model is applied to new dataset to predict pressure drop and efficiency of separation. When not within the limits, instead a separate MLA is implemented to construct predictive models.

4. STATISTICAL VALIDATION

Prediction performance model created by MLAs is to be statistically validated. Different statistical criteria exist for validating the prediction. Three statistical parameters Mean Average Error (MAE), Correlation Coefficient (CORR) and Root Mean Square Error (RMSE) are important statistical parameters to validate the model according to previous prediction studies. [46-48]. MAE and CORR will assess the reliability of the prediction of MLAs rather than the other statistical parameters and these two parameters are inversely proportional to the need for MAE to be as minimal as possible and CORR to be as close to one [49]. For all 8 traditional MLAs, therefore, MAE and CORR are evaluated for both pressure drop and separation efficiency of all six models of cyclone separators using the equations (5)-(8).

$$MAE_{\Delta P} = \frac{1}{n}\sum(\Delta P_{obs} - \Delta P_{pred}) \qquad -(5)$$

$$MAE_{\eta} = \frac{1}{n}\sum(\eta_{obs} - \eta_{pred}) \qquad -(6)$$

$$CORR_{\Delta P} = \frac{\frac{\sum(\Delta P_{pred} - \overline{\Delta P_{pred}})(\Delta P_{obs} - \overline{\Delta P_{obs}})}{n-1}}{\sqrt{\sum\frac{(\Delta P_{pred} - \overline{\Delta P_{pred}})^2}{n-1}\sum\frac{(\Delta P_{obs} - \overline{\Delta P_{obs}})^2}{n-1}}} \qquad -(7)$$

$$CORR_{\Delta P} = \frac{\frac{\sum(\eta_{pred} - \overline{\eta_{pred}})(\eta_{obs} - \overline{\eta_{obs}})}{n-1}}{\sqrt{\sum\frac{(\eta_{pred} - \overline{\eta_{pred}})^2}{n-1}\sum\frac{(\eta_{obs} - \overline{\eta_{obs}})^2}{n-1}}} \qquad -(8)$$

5. RESULT AND DISCUSSION

Predictive analysis is performed in the data analytics software Rapid miner studio v9.7.0 using eight traditional MLAs to predict performance of all six cyclone separator models. Training dataset is prepared from CFD analysis performed in Ansys fluent 18.1 for this predictive analysis. Three inputs are provided to MLAs that are used to design the cyclone separator since both the pressure drop parameter performance and the efficiency of separation depend on the design, they are: designed Cyclone Separator inlet velocity, separator volume flow rate that can be handled and the CFBC boiler chosen cyclone separator model.

5.1 Validation of Machine Learning

MLAs was statistically checked by two parameters CORR and MAE. For prediction models generated by eight typical MLAs, these two parameters are calculated for both the efficiency of separation of output parameters and the pressure drop. Statistical analysis of eight MLAs for the estimation of separation efficiency is shown in Figure 8.It shows that the MAE value is minimum, and when compared with other MLAs, CORR is maximum for Neural Network (NN).Similarly, for Gaussian Process (GP), statistical comparison for pressure drop in shown in Figure 9 where MAE is minimum for Neural Network (NN) and CORR is maximum. However, the validating conditions in the previous study state that only CORR accepts the pattern, and MAE has a lower value [49]. From Figure 9 it clearly shows that this pattern is observed only by Neural Network (NN). Hence, the Neural Network (NN) created an effective model of prediction compared to other MLAs.

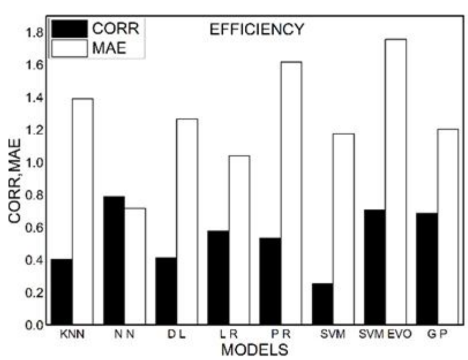

Figure 8: Statistical Comparison of Efficiency Prediction Model from various Machine Learning Algorithm

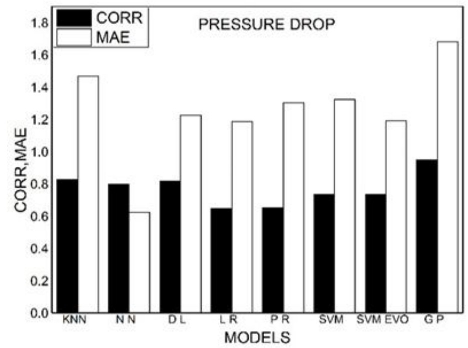

Figure 9: Statistical Comparison of Pressure Drop Prediction Model from various Machine Learning Algorithm

Neural network (NN) design of the MLA working network is shown in Figure 10. Network consists of a single, hidden layer for prediction model processing. The network is solved with forward propagation method for estimating output parameters[50, 51]. Neural Network threshold functions are used in single hidden layer forward propagation to improve the robustness and accuracy of parameter prediction[52]. Threshold node and input are generated in this network automatically[53,54].

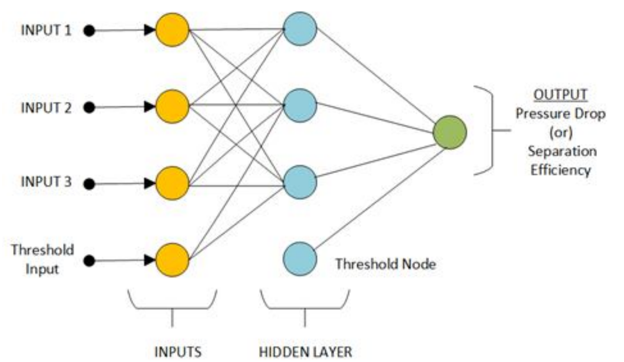

Figure 10: Neural Network Model for Prediction of Cyclone Separator Performance

5.2 Swift HT

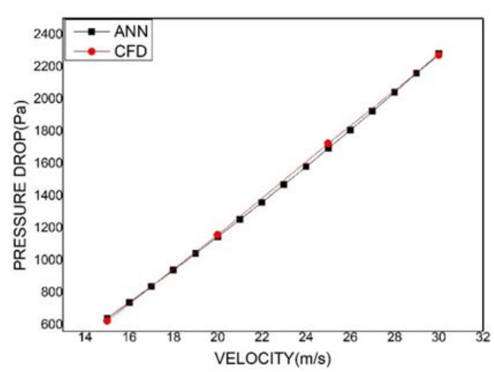

Figure 11: Comparison of Neural Network Prediction and CFD analysis of Pressure Drop in Pa with respect to inlet velocity in m/s of Swift HT model cyclone separator

The prediction model of the neural network is compared with the data collection of the Swift HT model for CFD analysis shown in Figures 11 & 12. In Figure 11, the pressure drop is directly proportional to the velocity of the inlet, both approaches obey the same pattern and converge for the whole range of velocities. Separation efficiency in Figure 12 decreases linearly with respect to inlet velocity, in both cases they follow similar trends and intersects for specific velocity ranges from 22 m/s to 25 m/s for other velocity deviation is very minimal.

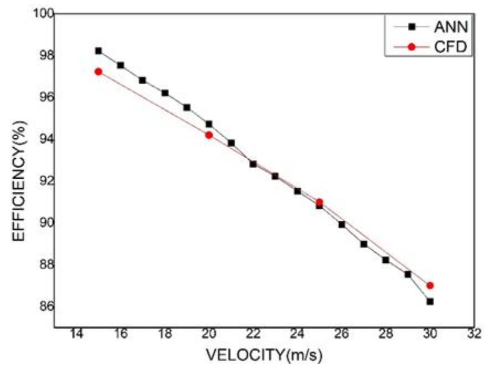

Figure 12: Comparison of Neural Network Prediction and CFD analysis of Efficiency in % with respect to inlet velocity in m/s of Swift HT model cyclone separator

5.3 Stairmand HT

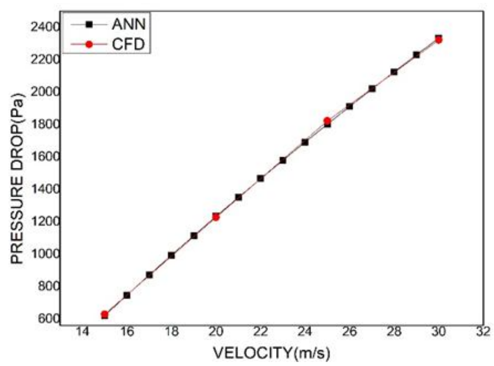

Figure 13: Comparison of Neural Network Prediction and CFD analysis of Pressure Drop in Pa with respect to inlet velocity in m/s of Stairmand HT model cyclone separator

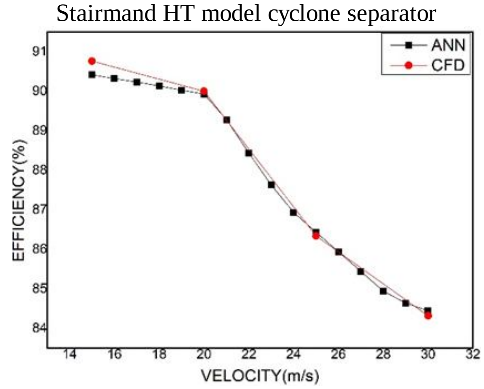

Figure 14: Comparison of Neural Network Prediction and CFD analysis of Efficiency in % with respect to inlet velocity in m/s of Stairmand HT model cyclone separator

Figures 13 & 14 show comparison of the predictive model and CFD analysis for the Stairmand HT cyclone separator. In Figure 13 the pressure drop for both models increases linearly with the inlet velocity and overlaps for considered velocity range. In Figure 14, separation efficiency decreases linearly with velocity up to 20 m/s, then the separation efficiency drops suddenly until 30 m/s. The two curves converge after inlet velocity is 20 m/s.

5.4 Swift HE

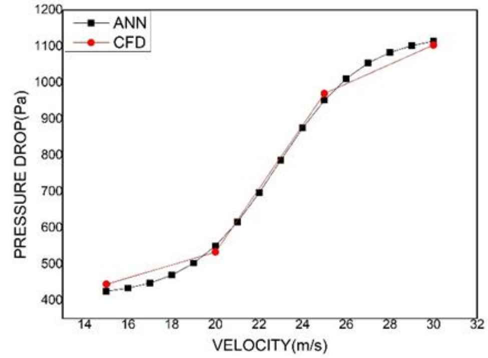

Figure 15: Comparison of Neural Network Prediction and CFD analysis of Pressure Drop in Pa with respect to inlet velocity in m/s of Swift HE model cyclone separator

The pressure drop and separation efficiency of the prediction for the swift HE cyclone separator is compared to the results of the CFD analysis shown in Figures 15 & 16. In Figure 15, both prediction and CFD models form a Sigmoid curve that overlaps one another for inlet speeds from 20 m/s to 25 m/s. In Figure 16 both models form a sigmoid curve for inlet speeds from 15 m/s to 25 m/s, and then decrease linearly to 30 m/s. Prediction model curve merely traces the curve of the CFD analysis.

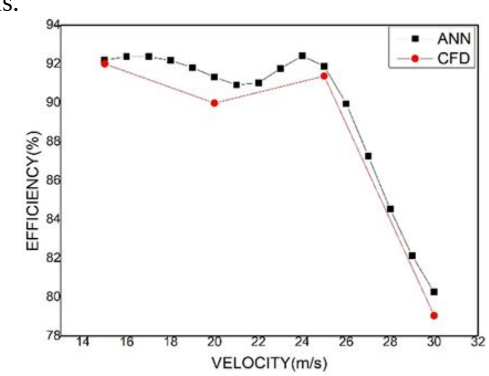

Figure 16: Comparison of Neural Network Prediction and CFD analysis of Efficiency in % with respect to inlet velocity in m/s of Swift HE model cyclone separator

5.5 Stairmand HE

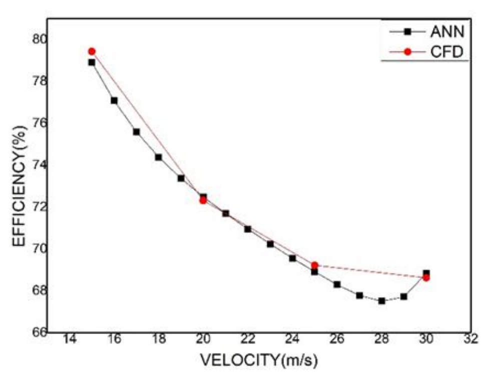

Figure 17. Comparison of Neural Network Prediction and CFD analysis of Pressure Drop in Pa with respect to inlet velocity in m/s of Stairmand HE model cyclone separator

With Neural Network MLA, the efficiency of the Stairmand HE model cyclone separator is expected, compared with the CFD analysis as shown in Figures 17 & 18. In Figure 17, the pressure drop of Stairmand HE in CFD analysis is linear in nature and almost constant, but prediction model shows an increase in pressure drop relative to inlet speed. In Figure 18 both methods follow similar trend and overlap between them for ranges from 20 m / s to 25 m / s for the velocity.

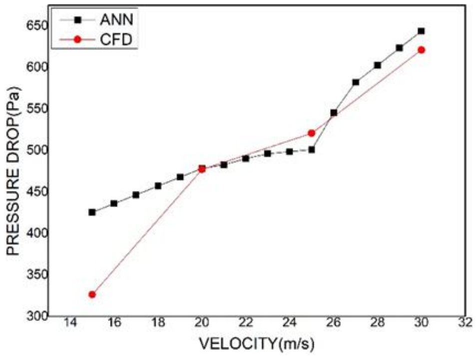

Figure 18: Comparison of Neural Network Prediction and CFD analysis of Efficiency in % with respect to inlet velocity in m/s of Stairmand HE model cyclone separator

5.6 Swift GP

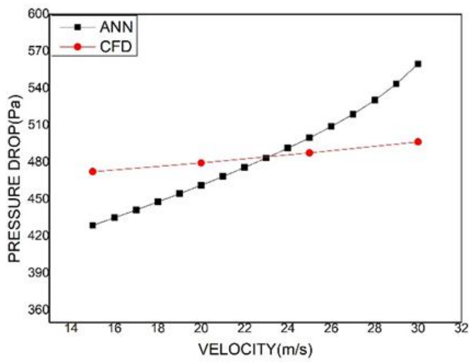

Figure 19: Comparison of Neural Network Prediction and CFD analysis of Pressure Drop in Pa with respect to inlet velocity in m/s of Swift GP model cyclone separator

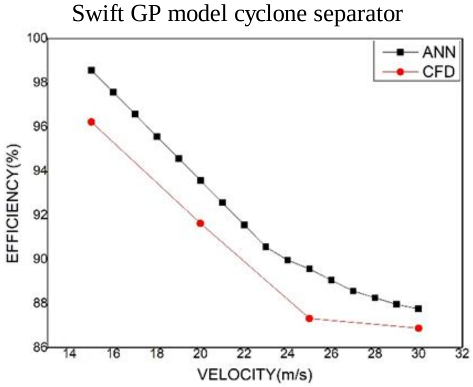

Figure 20: Comparison of Neural Network Prediction and CFD analysis of Efficiency in % with respect to inlet velocity in m/s of Swift GP model cyclone separator

The variation in pressure drop and separation efficiency with respect to inlet velocity is shown in Figures 19 and 20 for the CFD analysis and Neural Network prediction model for swift GP cyclone separator models. In Figure 19 both models have increased pressure drop pattern with respect to inlet velocity with two separate paths and converge at 20 m / s and 26 m / s respectively. In Figure 20 both models have declining pattern of velocity-related separation efficiency and Neural Network prediction model mimics the CFD study and forms a parallel line with more variance to each other.

5.7 Lapple GP

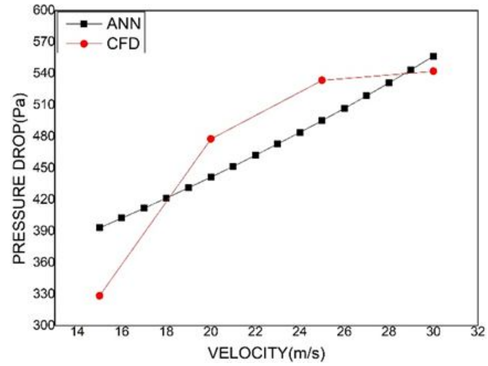

Figure 21: Comparison of Neural Network Prediction and CFD analysis of Pressure Drop in Pa with respect to inlet velocity in m/s of Lapple GP model cyclone separator

Comparison of Lapple GP's predictive model of the Neural Network and CFD analysis for both pressure drop and separation efficiency is shown in Figures 21 and 22, respectively. In Figure 21 the pressure drop increases as the velocity of the inlet increases for both the CFD model and the prediction model, but it follows the different paths and predicts correct values only at 18 m / s and 29 m / s which is not reliable. Likewise, the efficiency of the separation in Figure 22 decreases as the inlet velocity increases. Both models follow the same trend with different models and predict the exact value from 28 m / s to 29 m / s which cannot be reliable

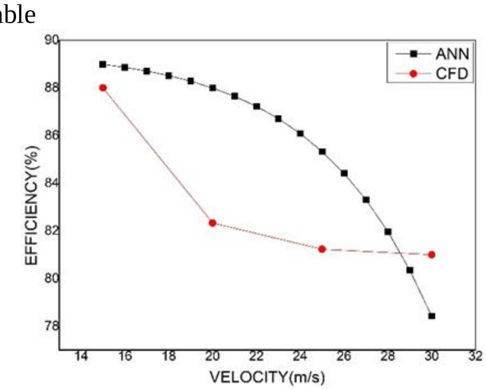

Figure 22: Comparison of Neural Network Prediction and CFD analysis of Efficiency in % with respect to inlet velocity in m/s of Lapple GP model cyclone separator

6. CONCLUSIONS

This research work is an attempt to construct a predictive model using MLAs for predicting performance of cyclone separators. To narrow down a single model of Machine Learning Algorithm for all six types of cyclone separator used in CFBC boilers. All six models are designed in SOLIDWORKS 2016 and Ansys fluent 18.1 conducts CFD analysis by varying inlet velocity from 15m/s to 30 m/s with a 5 m/s interval. A predictive analytics software Rapid miner studio v9.7.0 is utilized to predict separation efficiency and pressure drop of cyclone separator by using MLAs for the dataset generated in CFD analysis.

1. Two parameters Correlation coefficient (CORR) and Mean Average Error (MAE) are used for Statistical validation of traditional MLAs. By validation conditions Neural Network (NN) is better than other MLAs for predicting both the efficiency of separation and the cyclone separator pressure drop. Neural Network has CORR values as 0.788 & 0.798 for separation efficiency and pressure drop respectively. Similarly, the MAE values as 0.716 & 0.624 respectively. Neural Network alone is following the pattern as CORR is larger than MAE.

2. When applying NN MLA for the Swift HT model cyclone separator, it predicts pressure drop exactly as CFD analysis and separation efficiency predicts only about 20 m/s to 25 m/s inlet velocity. In other velocities percentage error in prediction ranges from 0.55% to 0.87% which is very negligible.

3. When applying NN MLA for the Stairmand HT model cyclone separator, it predicts the pressure drop across cyclone separator for all considered velocities close to CFD analysis. Similarly, separation efficiency prediction matches the CFD study for velocities ranging from 20 m/s to 30m/s. For other velocities percentage of error in prediction is approximately 0.1% to 0.38% which is very insignificant.

4. When applying NN MLA for Swift HE model cyclone separator pressure drop prediction matches CFD analysis for velocity ranges from 20 m/s to 25 m/s in other ranges percentage of predicted error is 0.9% to 4.3%. For separation efficiency prediction follows the same pattern as CFD analysis with percentage of error varying from 0.22% to 1.5%.

5. When using NN MLA for Stairmand HE model cyclone separator pressure drop predictions are not acceptable with CFD analysis dataset and when comparing for separation efficiency prediction model follows the similar trend of CFD analysis matches exactly in velocity ranges 20 m/s to 25 m/s in other ranges percentage of error is estimated as 0.23% to 0.64%.

6. When applying NN MLA for the Swift GP model cyclone separator pressure drop predictions do not display similar pattern and total contrast to the dataset of CFD analysis. When comparing for separation efficiency prediction similar patterns occur with CFD analysis dataset with a percentage of error varying from 1% to 2.6%.

7. While applying NN MLA to the cyclone separator model Lapple GP, both pressure drop and separation efficiency do not suit the dataset of CFD analysis.

8. For High Throughput (HT) models the cyclone separator pressure drop is predicted exactly by NN MLA. Only HT model cyclone separators have D_v/D_{cy} ratio greater than 0.5. Thus, Neural Network (NN) can predict the drop in pressure for any cyclone separator conFigureuration with D_v/D_{cy} ratio greater than 0.5.

9. Except for Lapple GP model, Neural Network (NN) predicts all other models separation efficiency with minimal deviation. In cyclone separator design S/D_{cy} ratio is less than 2 except for Lapple GP. Neural Network (NN) can therefore predict separation efficiency for any cyclone separator design with S/D_{cy} is less than 2.

7. NOMEMCLATURE

CFBC	Circulating Fluidized Bed Combustor
CFD	Computational Fluid Dynamics
HE	High Efficiency
HT	High Throughput
GP	General Purpose
MLA	Machine Learning Algorithm
MLAs	Machine Learning Algorithms
ML	Machine Learning
AI	Artificial Intelligence
MAE	Mean Average Error
$MAE\Delta P$	Mean Average Error of Pressure Drop
$MAE\eta$	Mean Average Error of Separation Efficiency
CORR	Correlation Co-efficient
$CORR\Delta P$	Correlation Co-efficient of Pressure Drop
$CORR\eta$	Correlation Co-efficient of Separation Efficiency
RSME	Root Mean Square Error
ANN	Artificial Neural Network
NN	Neural Network
LR	Linear Regression
PR	Polynomial Regression
GP	Gaussian Process
SVM	Support Vector Machine
SVM EVO	Support Vector Machine Evolutionary
KNN	K- Nearest Neighbour
DL	Deep Learning
RSM	Reynolds Stress Model
RANS	Reynolds-Average continuity and Navier-Stokes
Q	Volume flow rate
vi_n	Velocity inlet of cyclone separator
Ai_n	Inlet duct area
D	Depth of inlet duct
B	Breath of inlet duct
D_{cy}	Diameter of cyclone separator
D_v	Diameter of vortex finder
H_v	Height of vortex finder
S	Height of cyclone separator cylinder
H	Overall Height of Cyclone separator
E	Diameter of solid outlet pipe
P_{in}	Pressure at the inlet of cyclone separator
P_{out}	Pressure at the outlet of cyclone separator
ΔP	Pressure difference across cyclone separator
ΔP_{obs}	Pressure difference across cyclone separator

	estimated in CFD analysis
ΔP_{pred}	Pressure difference across cyclone separator predicted by MLAs
$\Delta \bar{P}_{obs}$	Mean value of Pressure difference across cyclone separator estimated in CFD analysis
$\Delta \bar{P}_{pred}$	Mean value of Pressure difference across cyclone separator predicted by MLAs
η_{sep}	Separation Efficiency of Cyclone Separator
n	Number of terms
n_{ip}	Number of particle incomplete
n_{tp}	Number of particles trapped

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