I. J. Engineering and Manufacturing, **2024, 1, 53-65**
Published Online on February 8, 2024 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijem.2024.01.05

AI-Based Smart Prediction of Liquid Flow System Using Machine Learning Approach

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Received: 16 August, 2023; Revised: 08 September, 2023; Accepted: 15 October, 2023; Published: 08 February, 2024

Abstract: Predicting the liquid flow rate in the process industry has proved to be a critical problem to solve. To develop a mathematical, in-depth of physics-based prognostics understanding is often required. However, in a complex process control system, sometimes proper knowledge of system behaviour is unavailable, in such cases, the complement model-based prognostics transform into a smart process control system with the help of Artificial Intelligence. In previous research a number of prognostic methods, based on classical intelligence techniques, such as artificial neural networks (ANNs), Fuzzy logic controller, Adaptive Fuzzy inference system (ANFIS) etc., utilized in a liquid flow process model to predict the effectiveness. Due to system complexity, Computational time &over fitting the performance of the AI has been limited. In this work we proposed three machine learning regression model: Random Forest (RF), decision Tree (DT) & linear Regression (LR) to predict the flow rate of a process control system. The effectiveness of the model is evaluated in terms of training time, RMSE, MAE & accuracy. Overall, this study suggested that the Decision Tree outperformed than other two models RF & LR by achieving the maximum accuracy, least RMSE & Computational time is 98.6%, 0.0859 & 0.115 Seconds respectively.

Index Terms: Liquid flow process, Modeling, Machine learning, Regression analysis

1. Introduction

Smart process control system aims to integrate artificial intelligence, high-performance computing, advance analytical method & the industrial internet of things into the process industry to create high-quality products within fewer amounts of time, effort & cost. A smart process control system in cooperate the information of interoperable & sensor networks to the intelligent system to monitoring the process variable in such a manner to get the optimum output response variable. To improve the system reliability, reducing maintenance cost, determine the condition of the in-service system & obtain the desired process output it is crucial to develop the model using artificial intelligence. In most of the process control system three different level of intelligent control techniques utilized e.g., logical level, logical reactive level & neuro reactive level shown in Figure 1. All types of observation of any process system relied upon these three levels of intelligent control level & generate the control output. As the intelligent control system improves computation time significantly reduce &fit best with the actual process model.

Improvement of the AI model complexity, computational time & avoiding of the over fitting are important parameters to choose an effective regression model. On basis of this in present research we proposed three machine learning regression models: Linear Regression, Decision Tree & random Forest to evaluating the performance of a liquid flow control process.

This paper narrates the application of Machine Learning model in liquid flow model system. The major objective of this paper is to unfold the merits of machine learning techniques in prediction of liquid flow in process model. Based on the systematic understanding industry the paper presents the workflows that utilize the machine learning and AI for effective computation and decision making. This paper highlights that how a hand-shaking between liquid flow process model and numerical simulator with machine learning model eases the work and advances the productivity.

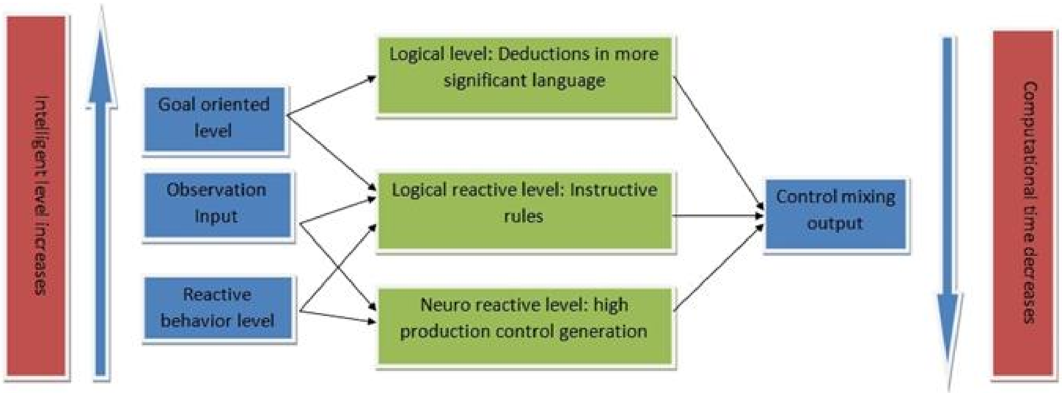

Fig.1.Various intelligent control level in Process control system

The rest of the paper is organized as follows: in "Literature Review", different flow sensor &AI model are described. In the section of proposed model, experimental setup of the process, mechanism, input & output process variables are given. In the section "methodology", describe the data preparation & conduction of the study elaborate. In the section "prediction of process parameters using machine algorithm", a brief description of three supervised algorithms namely linear regression, Decision tree & Random Forest regression analysis has been described. Finally, result in an analysis followed by a conclusion.

2. Literature Review

In-process control industry modeling of liquid flow is one of the best examples of a complex nonlinear system where model quality depends upon parameter estimation, characteristics flow sensor, model uncertainty, and computational burden. In process control industry researcher used a numerous of flow sensor depending upon the nature of the control process such as film pressure transducers [1], micro machined flow sensor[2], monolithic sensor[3], MEMS sensor[4], Thermal liquid flow sensor [5], Miniature liquid flow sensor [6], Piezoresistive flow sensor [7], Coriolis mass flow sensor [8], Pulsed thermal flow sensor [9], Vortex flow sensor [10], Electromagnetic flow sensor [11], Venturi flow sensor [12], Ultrasonic flow sensor [13], Turbine flow sensor [14], but due to better accuracy & response time for medium liquid flowrate hot film anemometer flow sensor [15] widely used.

Parametric optimization of the process control system is one of the important aspects of a smart liquid flow process system where different artificial intelligence is applied to get the best optimal output process variable & fit best with the experimental setup. In this research, there are several intelligence techniques, metaheuristic & bio-inspired optimization techniques utilized for designing the predictive model which fit best with an actual experimental model such of are a fuzzy logic controller [16] where both the input & output variables are designed depending upon types & number of membership functions. It has been observed triangular-type membership function offers better predictive results than other types of membership functions. A feedforward neural network model[17] was also proposed for liquid flow model with different sets of train & test datasets in MATLAB workspace. The liquid flow system has been designed with the help of two different nonlinear mathematical models ANOVA (analysis of variance) & RSM (response surface methodology) and finally, it has been optimized by Genetic Algorithm [18]. A neural network has been used to model a linear equation with the help of input & output variables and next phase Genetic algorithm (GA-ANN)[19] used to optimize to get best-fitted model. Except of metaheuristic algorithm there number of hybrid empirical model optimization technique also applied such as hybrid FPA – Analysis of variance (ANOVA)[20] to achieved the best fitted model.

Machine learning (ML) techniques widely applied to both regression & classification issues dependent on informational indexes from modern process operation or mathematical reenactments when the classical model is hard to acquire. Several studies were done by the research to apply the different supervised &unsupervised machine learning in different industrial process industry such of them are: oscillation detection[21], smarty process industry[22], minerals processing [23], industrial electrical tomography[24], fault detection of nonlinear processes[25], heavy process manufacturing [26], smart machining process[27], prediction of soil temperature[28], shear stress modeling [29], improvement of process quality in metallic materials [30], tool wear prediction [31], milling diagnosis[32], Robot assist process[33].

3. Proposed Model

The present research has been explained in this section. At first, the experimental datasets are prepared from the experimental set up of liquid flow control unit. In later subsections describe all the process parameters including input potential parameters as well as process output flowrate. To perform the experiment work we used an anemometer meter flow sensor & to detect the sensor output voltage we used a digital multimeter. Overall we get 134 datasets achieved which are divided into train (2/3 of total datasets) & validation (1/3 of total datasets) datasets. Figure 2 shows the modeling of the proposed liquid flow system.

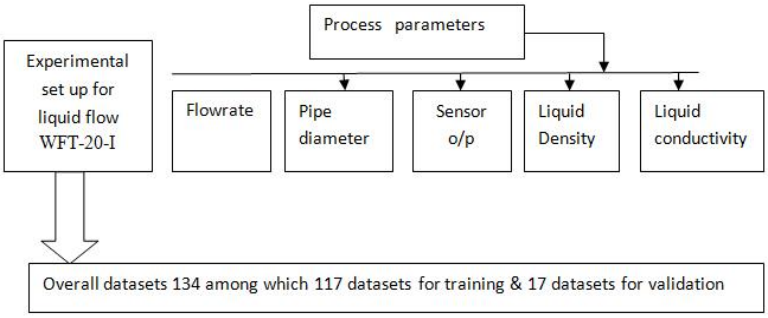

Fig.2.Modelling of the proposed liquid flow system

3.1. Experimental Setup

In this subsection, the experimental setup is shown in Figure 3(Model no. WFT-20-I) which includes a water tank, pump, anemometer type flow sensor, water reservoir, flow rate indicator & control valve. Except for these externally a contact type anemometer type flow sensor is utilized. The output of the flow sensor detects the voltages corresponding to flowrate & given set of liquid properties & pipe diameter.

Fig.3.Liquid Flow Measurement and Control Unit set up

3.2 Process Parameter

The experimental work is compassed in estimation & control of the Flow & Level of a liquid shown in Figure 3. In the present inspection, we used liquid flowrate ranging from 0Lpm -600Lpm. When this liquid passing through the sensor it provides the voltage in the range of milivolt. Sensor output voltage ranging also concern about the pipe diameter & other liquid properties [19]. Table 1&Table 2 shows the experimental setup & miscellaneous components & ranging of potential independent input variables.

Table 1.Experimental Setup [20]

Components	Specification
Flow & Level measurement and Control	Model no. WFT -20-I
Flow sensor	Constructed by SL 100 transistor
Diameter of PVC pipe	20mm,25mm & 30mm
Digital Multimeter	3 ½
Rota meter	Taking the reading of the Flow rate ranging 0-600 Lpm

Table 2. Ranges of the process parameters [20]

Independent parameters	Ranges with units
Sensor output	210 mv – 285 mv
Pipe diameter	20mm, 25mm & 30mm
Water conductivity	606,615 & 622(W/m.k)
Water Viscosity	725.4,779.7 &898.2 µpas.sec
Water Density	993.9,995.6&996.9kg/m3

4. Methodology

The objective of the investigation is to build up a AI model that anticipates with worthy exactness and without the requirement for physical tests, the values of pipe diameter, flow sensor output voltage & liquid characteristics.

	sensor output	diameter	conductivity	viscosity	flow rate
0	0.214	0.025	606.5	898.2	0.0000
1	0.216	0.025	606.5	898.2	0.0008
2	0.218	0.025	606.5	898.2	0.0016
3	0.219	0.025	606.5	898.2	0.0024
4	0.225	0.025	606.5	898.2	0.0032

Fig.4. Data structure of the process variables

The best possibility to grow such an effective model is the utilization of Machine Learning calculations, that was exhibited to foresee with high exactness, new yields and choices by learning the shrouded highlights in existing information[21]. For deploying & validation of the Supervised Learning Methods we used 134 numbers of experimental datasets. Input attributes & their description is shown in Table 3 & Figure 4 while Figure 5 shows the flowchart of the overall process.

Table 3. Represent the four input attributes used for model formation & validations

Si No	Attributes	Description	Values
1	Pipe Diameter	Three different sets of pipe diameter taken	Continuous value
2	Sensor output	Wide ranges of flow sensor output voltage (in mv)	Continuous value
3	Conductivity	Three different sets of water conductivity	Continuous value
4	Viscosity	Three different sets of water viscosity	Continuous value
5	Flow rate	Liquid flow rate ranging from 0lpm to 600 Lpm	Continuous value

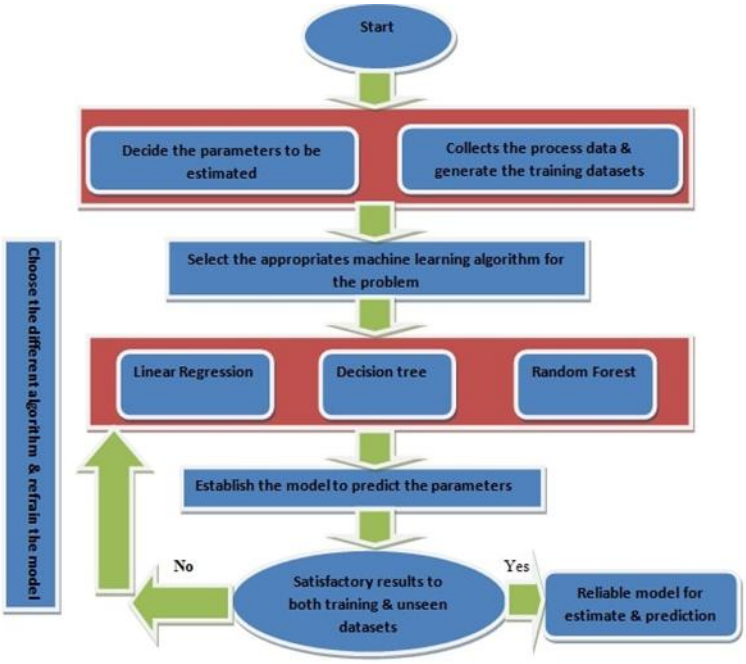

Fig.5. Basic flowchart of the Machine Learning Algorithm for Liquid Flow Model

4.1 Tools & Technique

To play out all these three algorithms we utilized the following features processor and platform: Intel i3, sixth era processor, OS: Ubuntu 20.04 and RAM 8 GB, python 3.7.6, and Jupyter journal 6.03. For a new arrangement of an input process variable in a liquid flow process system, we definitely get the new set of the output process variable, flow rate. Since we are finding the new flow rate on a similar test set up with a similar administrator and a similar process input variable, is the function of flow rate. In view of our process variables and process information, it was not muddled to make an investigation to choose some arrangement of attributes suspected to prompt parameter changes. This choice was additionally affirmed by checking the informational index estimations of pipe diameter, flow sensor output voltage, and liquid properties. Figure 5 showing the flowchart of the proposed research.

In the next two sections, we will perform predictions of liquid flow rate based on three models which are Decision tree (DT), linear regression (LR) &Random forest (RF)[34]& to the field of single-output regression. For a given set of potential input parameters we find out the calculated liquid flow rate by the above mentioned three machine learning algorithms & accuracy can be determined by the deviation between the calculated & experimental flow rate for a given set of inputs. However, to identify the based model, we will evaluate the two different statistical error values: Root mean square (RMSE) & Mean absolute error (MAE).

5. Prediction of Process Parameters

In this part, we will introduce the prescient models that we utilized for our research. All these three strategies (Linear Regression, Decision Tree & Random Forest) demonstrated better outcomes on our contextual investigation during our pre-tests. Finally, we chose to contrast them and calculate the best one which gives a superior forecast result on the approval information. The given problem is a regression type of problem, the reason we have used 3 main types of regression algorithms. They are listed as below:

1. Linear Regression (LR)
2. Decision Tree Regression (DT)
3. Random Forest Regression (RF)

The results obtained after using the above algorithms are described individually. The data visualization part for all the algorithms is the same, which tells us, rather confirms the linearity and the continuous data.

5.1 Decision Tree Regressors

As already discussed, the data visualization and the heat map of the given datasheet are the same, and accordingly, after analyzing the plot, it is confirmed as the regression type of problem. In order to obtain some better accuracy, we are applying the Decision Tree Regressors. This can perform both regression and classification tasks [35]. It is a tree-organized classifier with three sorts of hubs. The Root Node is the underlying hub that specifies the whole example and may part assist in various hubs shown in Figure 6.

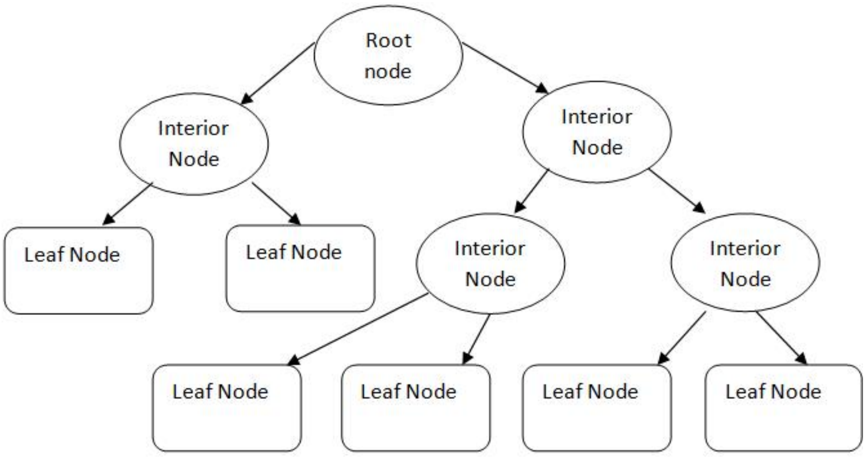

Fig.6. Flowchart for the hierarchical Decision Tree Algorithm

The Interior Nodes represent an informational index and the branches to the choice of principles [36]. At last, the Leaf Nodes specify to the result. This calculation is helpful for tackling choice related issues. With a specific information point, it is run totally through the whole tree by noting True/False inquiries until it arrives at the leaf hub. The last expectation is the normal of the estimation of the reliant variable in that specific leaf hub. Through various emphases, the Tree can anticipate an appropriate, an incentive for the information point [37]. Choice trees have a bit of leeway that it is straightforward, lesser information cleaning is required, non-linearity doesn't influence the model's exhibition and the number of hyper-boundaries to be tuned is practically invalid [35].

6. Result Analysis

In the liquid flow control framework, crude information gathered from the element extraction measure and changed over into a lot of factual highlights in an arrangement upheld by AI calculations. The factual highlights are then given as a contribution to an AI Algorithm. In this investigation, the process information was gathered from (1) sensor yield voltage, (2) pipe diameter, (3) fluid thickness, and (4) fluid conductivity. A lot of factual highlights were separated from these potential information boundaries as recorded in Table 4. The statistical metrics of each input & output variables are reflected in Table 4. Data visualization of the potential input parameters also shown in Figure 7.

Table 4. List of extracted features by machine learning

Parameters	Maximum	Mean	Standard deviation
Sensor output	0.2850	0.238398	0.017398
Pipe diameter	0.0300	0.025086	0.003963
Liquid viscosity	898.20	737.8079	235.9209
Liquid conductivity	0.0096	562.2621	172.9209

6.1 Performance measure:

Three prescient models were created utilizing linear relapse, Decision tree, and Random Forest separately. Out of total information datasets, 2/3 (89 sample data sets) chosen for model train datasets (preparing) & the rest (1/3) of datasets were utilized for model validation (testing). Figure. 8 to Figure 10 show the anticipated against actual liquid flow rate with the calculated flowrate utilizing LR, DT, and RFs, separately where it is clearly shown that DT is outperformed as best fitted of actual flowrate & predicted flowrate data points. Table 5 shows the comparative study of the training time for linear regression, Decision Tree, and RFs, respectively in a liquid flow process system. From comparative study it has been observed that least computational time is taken by Decision Tree. Figure 11 shows the computational time comparison based on training & validation time for LR, DT & RF.

Table 5. Comparative study of LR, DT & RF based on Training Time

Name of the algorithm	Training time in Sec.
Linear regression	0.438
Decision tree	0.115
Random Forest	0.615

Figure 12 to Figure 14 shown the different statistical comparison: Accuracy, RMSE & MAE between these three algorithms: Linear regression, Decision Tree, and RFs respectively [35]. Table 6, Table 7& Table 8 representing comparative study of algorithms based on Accuracy, RMSE & MAE. Maximum accuracy obtained by Decision Tree algorithm attend about 98.62% and least RMSE is 0.0859 but least MAE is obtained by Logistics Regression is about to 0.0744. Figure 11 to Figure 14 represent their graphical comparison. Figure 11 shows computational time for training & testing dataset for all the algorithm. During testing dataset computational time is least for LR algorithm. An expansion in the number of cases inside these classes will be significant to accomplishing a more homogeneous exactness over all classes and that expectations are dependable enough to take care of into the Adaptive Model [38].

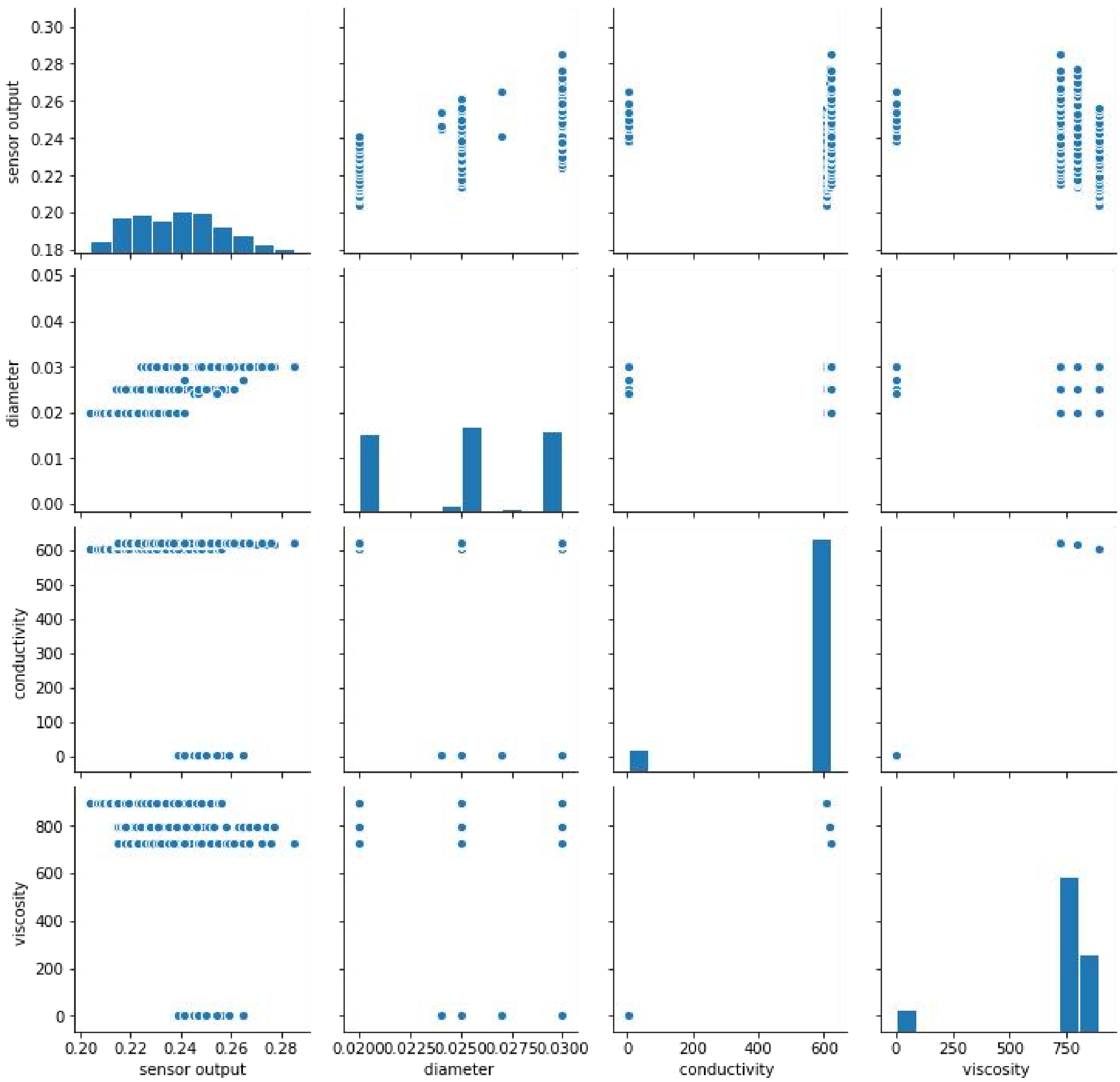

Fig.7. Data visualization for liquid flow model in machine learning

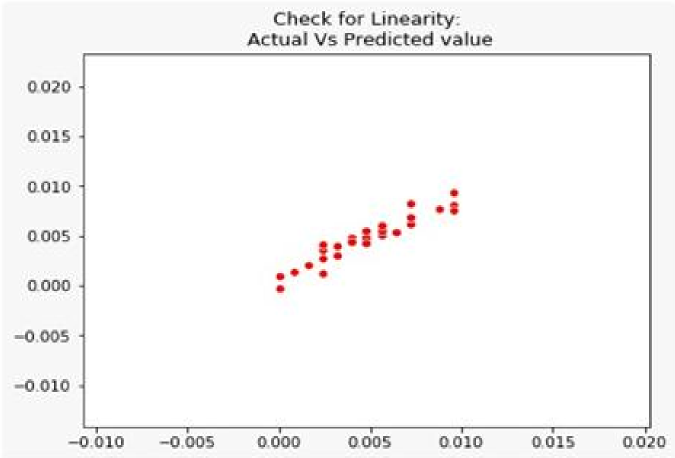

Fig.8. Actual vs. predicted flow rate in Linear Regression

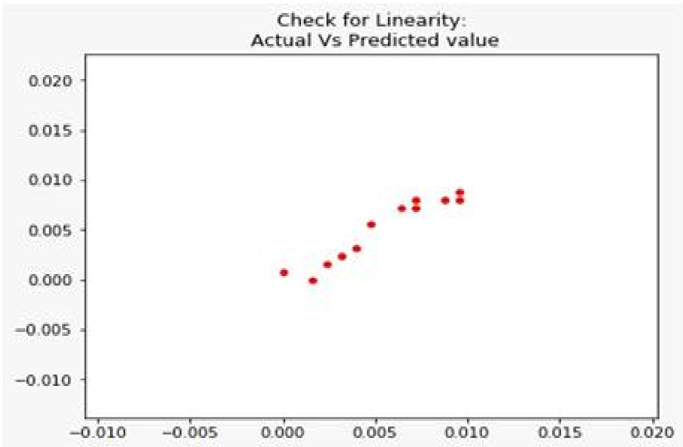

Fig.9. Actual vs. predicted flow rate in Decision Tree

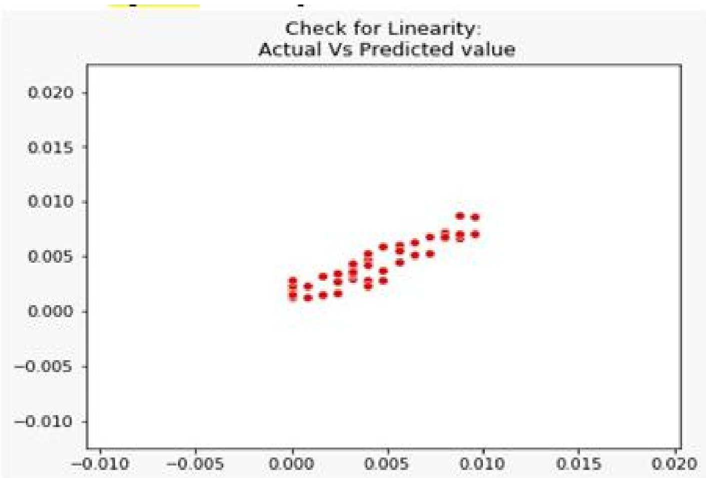

Fig.10. Actual vs. predicted flow rate in Random Forest

Table 6. Comparative study based on Accuracy

Algorithm used	Accuracy obtained
Linear Regression	90%
Decision Tree Regression	98.6%
Random Forest Regression	78.40%

Table 7. Comparative study based on RMSE

Algorithm used	RMSE
Linear Regression	0.0891
Decision Tree Regression	0.0859
Random Forest Regression	0.1340

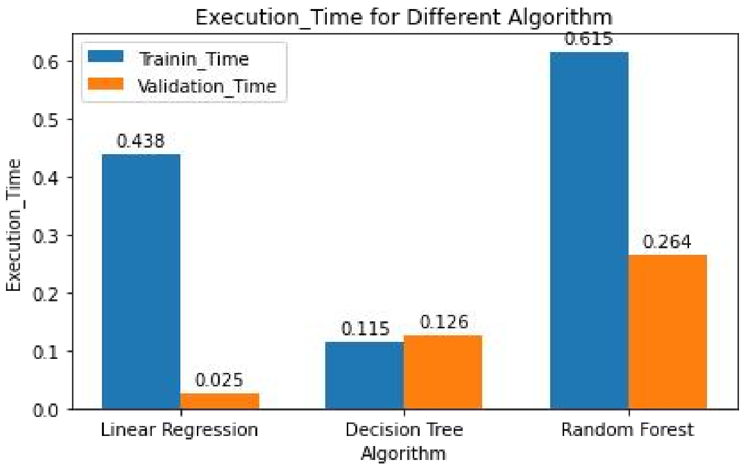

Fig.11.Comparative study based on computational time for LR,DT & RF

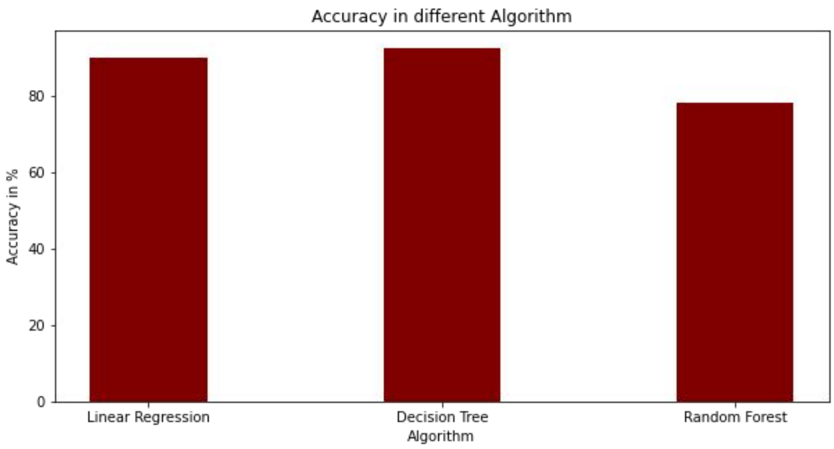

Fig.12. Comparative study based on Accuracy for LR, DT & RF

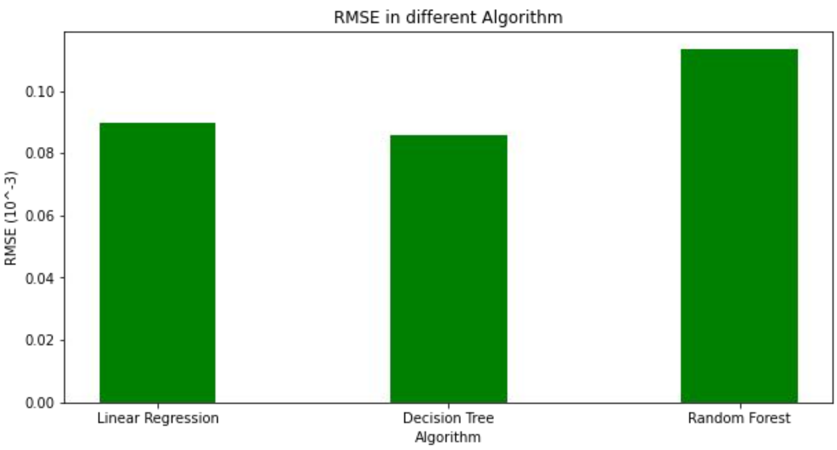

Fig.13. Comparative study based on RMSE for LR, DT & RF

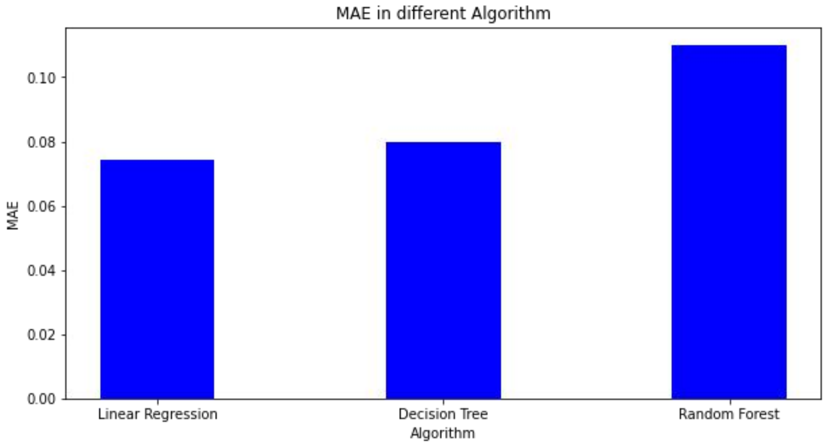

Fig.14. Comparative study based on MAE for LR, DT & RF

Table 8. Comparative study based on MAE

Algorithm used	MAE
Linear Regression	0.0744
Decision Tree Regression	0.0799
Random Forest Regression	0.110

Now, we summarize the performances score of all these three machine learning algorithms based on training time, accuracy, RMSE & MAE. Performance score of each criterion is determined as the proportion of the algorithm accomplishes the best outcome (rule) to the complete number of the calculation. The algorithm which achieves the best result score 0.66, medium result score 0.33 & least performance algorithm score 0. Table 9 shows the performance score of each algorithm.

Table 9. Performance score of each Algorithm

Algorithm	Training Time	Accuracy	RMSE	MAE	Total score
LR	0.33	0.33	0.33	0.66	1.66
DT	0.66	0.66	0.66	0.33	2.31
RF	0	0	0	0	0

6.2 Comparison with existing System:

In this section proposed model reliability verified against state-of-the-art existing systems explain in Table 10

Table 10. Comparative study between proposed models with existing model

Source	Algorithm/ Technique	Maximum Accuracy
[16]	Fuzzy logic Model	92.02
[43]	ANN model	97.06
[21]	Hybrid GA-ANN	98.42
[22]	ANFIS	97.857
Present research	Random Forest, Decision Tree & Linear regression	98.6%

In present research we used three regression models where Decision Tree achieves the maximum accuracy of 98.6% outperformed than the other state-of –art existing model.

7. Conclusion & Future Work

Controlling of liquid flow is a one of the important parameters in process industry. Improper parameter setting in any liquid process industry can damage the system. In this research we collect 134 number of datasets from the experimental setup &segmented into two modules as train & test datasets. To avoid the over fitting, reduction in computational time & model complexity in this research we proposed three Machine learning regression model: Decision Tree, Random Forest & Linear Regression to predict the model output.

The performance measures using statistical analysis include accuracy, mean squared error, mean absolute error, and training time is better for Decision Tree algorithm than LR & RF while the performance of Mean absolute error (MAE) & model Validation time is poor for DT than the LR. The overall result analysis concludes two main points: (1) Machine learning Decision Tree can predict the flow rate in liquid flow control processes very accurately and (2) we compared the performance of DT with that of LR & RF observed that DT outperform LR & RF for this particular application example. (3) Present research outperformed the previous model utilized in same data structure & experimental set up. This method is applicable for any type of process control system where a given set of appropriate input parameters predict the process output accurately. In other words, to apply this method the learning component needs to be trained on the behavior of the combination of the selected input parameters. Hence this model can be easily implemented & it offers a higher degree of accuracy of the prediction.

In the future, a comparative study between the performances of LR, DT & RF with some advanced type of ANNs, like recurrent neural networks (RNN) can be conducted. Besides of this hybrid Algorithms like feature selected GA optimized RF algorithm may be another option for future study. However, implementation of IoT based AI model in a process industry will be the future scope of the present research.

Conflicts of interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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How to cite this paper: Pijush Dutta, Gour Gopal Jana, Shobhandeb Paul, Souvik Pal, Sumanta Dey, Arindam Sadhu, "AI-Based Smart Prediction of Liquid Flow System Using Machine Learning Approach", International Journal of Engineering and Manufacturing (IJEM), Vol.14, No.1, pp. 53-65, 2024. DOI:10.5815/ijem.2024.01.05