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Machine Learning Based Decision-Making Model to Determine Size of Micro Nano Bubble

Pinisetti Swami Sairam, Ravi Gunupuru, Jitendra K Pandey

Abstract*: Machine learning has been widely used for large data processing with varied scope of application aspects. In this paper machine learning is used to determine the size of air bubbles that can be generated in an optimal condition of various parameters such as gas flow rate, water temperature and operating pressure of the system. Air bubbles have significant role to play when it comes to water treatment. Bubbles having significance in volume are proportionally valued when it comes to extent of treatment. The research concludes with a conceptual model influenced by machine learning approach that can estimate best combination of the parameter that are feasible for generation of most efficient generation.

***Keywords*: Aeration, machine learning, micro nano bubbles, water treatment.**

I. INTRODUCTION

Machine learning (ML) has been gaining attention by many researchers for its potential applications in water treatment plants (WTPs). Traditional WTPs contains different processes of water treatment which includes sedimentation, aeration, filtration and disinfection [1]. Parameters such as turbidity, biological oxygen demand, chemical oxygen demand, total suspended solids and total dissolved solids vary at different stage of treatment process. Though several automation and control technologies are being used to develop a sustainable solution but modelling of these systems still remains as a challenge for its huge nonlinearity and change in system variables physically, chemically and biologically [1]. Aeration process of a WTP is considered to reduce most of the effluents present in any wastewater [2]. This process comprises of introducing air into water which in turns assists in reduction/removal of dissolved gases and oxidation of metal ions present in water. This process is used as an alternative solution of chemical treatment processes where different chemicals are used. Methods such as dissolved air flotation (DAF), mechanical aeration or combine aeration are used for introduction of air into water [3]. These processes usually consume huge energy due to use of heavy motors.

Micro nano bubble (MNB) technology is being researched as an alternative solution to replace these systems where gas bubbles ranging from 10nm to 30µm are introduced in water [4]. These bubbles, due to its smaller in size, contains large interfacial area, high retention time and slow rising velocity thereby enabling them for efficient diffusion of gas or air into the surrounding water. Studies reported an increase in dissolved oxygen (DO) levels using MNBs [5]. Few researchers have also observed rate of oxidation of metal ions present in water via MNB [6]. While MNBs have shown its potential for efficient removal of hazardous metal ions and other pollutants but parameters for generation of MNBs is yet to be narrated due to its operational challenges.

II. MNB GENERATION SETUP

Parameters such as system operational pressure, gas flow rate, gas type and water temperature play a vital role for generation of MNB. ML algorithms being effective for multi parameter modelling, can assist operators for effective decision making to enable generation of uniform sized MNBs under varying temperatures.

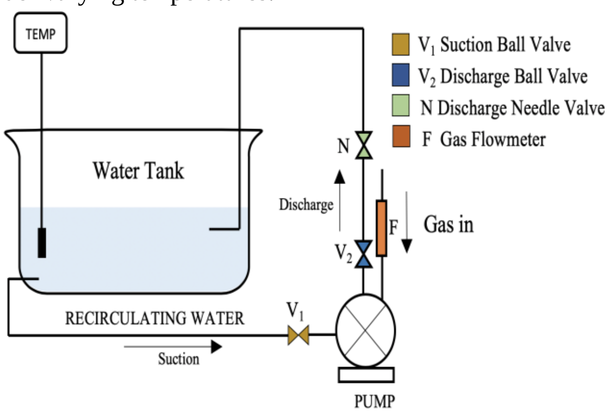

Fig. 1. Schematic of experimental setup

The system comprises of a water tank with a storage capacity of 40L, a multiphase induction pump KTM 20 (Nikuni, Japan), ball valves and gas flow meters. Temperature sensor in this system was used from Lutron. MNB size measurement was observed via Malvern S90. System was operated in a recirculating manner for a fixed volume of water (30L) for a duration of 5 min. MNBs were generated by adjusting the system parameters as discussed in table 1.

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* Correspondence Author
Pinisetti Swami Sairam*, Research Fellow, University of Petroleum and Energy Studies, Bidholi, Dehradun, Uttarakhand, Email:swami.sairam@gmail.com
Ravi Gunupurur, Department of Chemistry, University of Petroleum and Energy Studies, Bidholi, Dehradun, Uttarakhand, Email:ravibhuchem@gmail.com
Jitendra K Pandey*, University of Petroleum and Energy Studies, Bidholi, Dehradun, Uttarakhand, Email:jeetusnu@gmail.com

Table 1: Experimental Approaches

Parameters	Value
Inlet Pressure (V1)	-9 PSI, -3 PSI
Outlet Pressure (V2, N)	60 PSI, 80 PSI
Gas flow (F)	1 LPM, 0.30 LPM
Water Temperature	15°C to 35°C

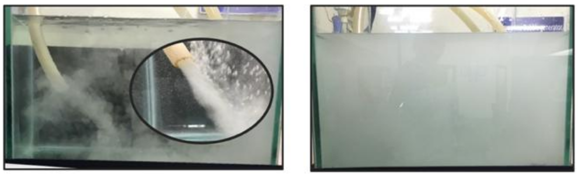

Fig.2. Generation of MNBs (a) immediately after starting the system for MNB generation; (b) after 5mins of MNB generation

During experimentation it was observed that the size of MNB varied for different operational parameters of the valves and further it used to vary w.r.t the temperature of water.

III. MACHINE LEARNING

ML algorithms methods are categorized as (a) regression and (b) classification method. System in which output variables are discrete in nature falls under classification algorithm [7]. However, systems where output variables vary continuously falls under regression algorithm models. Since the output of our system is varied continuously, regression algorithm is considered in this study for MNB size estimation parameters. Regression analysis approach is a process for estimating relationships between the variables effecting system [8]. These systems usually contain single output response based on multi or single input variable. There are different types of regression techniques typically applied depending on type of correlation between the variables. These include linear, polynomial and logistic.

In the stated application case though there are number of variables the behavior of the variables is primarily linear [8]. Of the different ways, for multi variable processing regression approaches typically aim for categorization. Classification methods at times support both continuous and categorical data with limited computational cost. In the stated application though the mechanism is prediction of specifications of parameters, it can also be visualized as classification of variables (ranges) to their respective type or volume of bubble (class). Hence Classification And Regression Tress (CART) is a effective method for this problem case [9].

Variable tendencies having linear behavior and non-deterministic approach decision systems (classifier) are typically used [9]. In the given context the number of variables considered are *water temperature, system pressures, gas type, gas flow rate*; indicate not only linear relation but also linear correlation. Hence initial and stable classifier (decision tree) with limited number of classes is considered [9]. The advantages of decision tree is stability with high dimensional data and stable accuracy. This inductive approach provided by the decision tree is very effective when no specificities on the domain knowledge is considered.

A. EXPERIMENTATION

Using the laboratory apparatus, the experimental setup is constructed and set as shown in figure 1. After running experimentation for 10 cycles of 5 mins each, information about behavior of various parameters at the respective valves and other non-behavioral parametric information is captured and tabulated as shown in below table 1.

Table 1: Sample parameters for decision tree

Sl.No	Water Temperature (°C)	System I/P Pressure (PSI)	System O/P Pressure (PSI)	Gas Flow Rate (LPM)
1	16	-1	60	1
2	19	-9	60	1
3	16	-1	60	0.3
4	19	-9	60	0.3
5	16	-1	80	1
6	19	-9	80	1
7	16	-1	80	0.3
8	19	-9	80	0.3

The experimentation as resulted in a dataset of 300 entities with a sample representation as listed in the table 1. To develop a decision making model, the data set is used a a preliminary and thereby decision tree is generated.

B. DECISION TREE

Through the help of decision tree (DT) methodology one can classify the value of a variable via multiple inputs [10]. This is achieved by designing a tree like structure comprising multiple leaf nodes and thereby multiple parts for the decisions. A typical DT consists of root node, splitter and decision node followed by fringe node. The root node is calculated based on 'gini' index [11]. Thereby DT is constructed as indicated in figure 2.

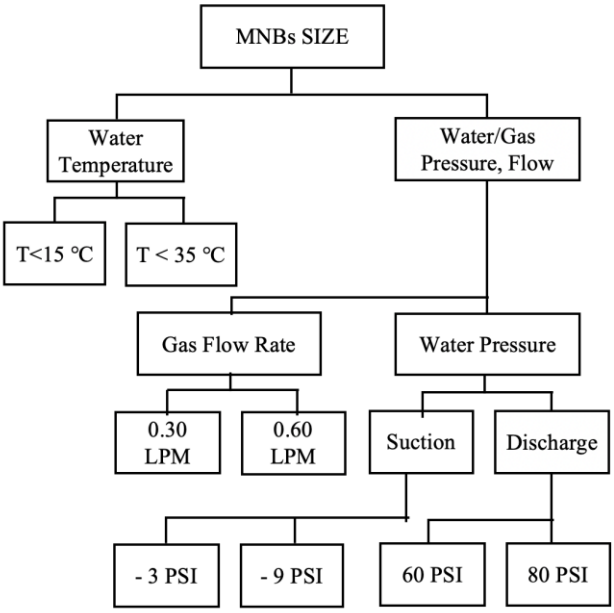

Fig.3. Decision tree of the system

Through the DT, initial experimentation was carried out for different sets of MNB generation w.r.t ambient air. However, specific gases such as O_2 and O_3 were also used individually to validate the system. Experimentations for MNBs generation for its size ranging between 500nm to 1500nm at different temperature regions were performed for a duration of 60 min.

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Parameter estimating for system operation were determined by DT. Figure 3 shows MNBs size generated during experimentation and it shows that ML can be an effective method to determine operational settings of the system.

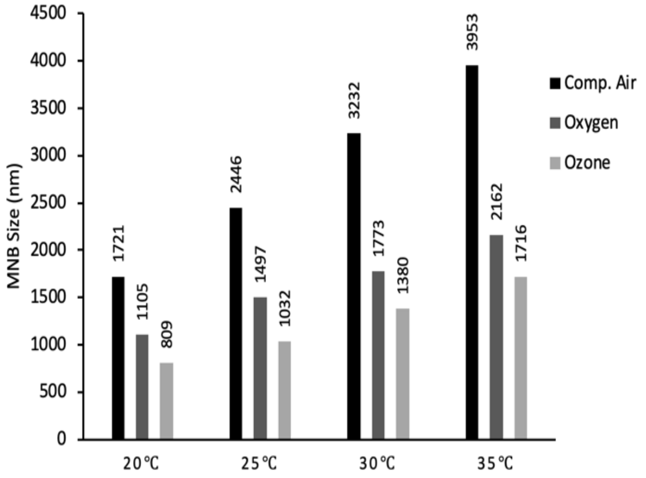

Fig.4. Size distribution of MNBs in pure distilled water at different operational conditions

The above graph indicates that the size of bubble can be reduced with a decrease in temperature. However, the rate of decrease is not continuous. Hence to maintain stable bubble size for a constant period of time it is necessary to stabilize the parameters and ensure the stability of the bubble.

IV. DISCUSSION

The data set generated is initially classified into testing and training sets and thereby 1/5th of the entities are listed under test set. The generated tree is being validated using the test set and is found 85% accurate based on the outcome. Though the model has indicated the availability of specific MNB, the system is not able to guarantee the continuous availability of MNBs in the specified amount of time during the circulation process. However it is necessary for water treatment process to generate a continuous MNB over a given period of time. Hence there is a further refinement in the selection of parameters along with their behavior to be considered for guaranteeing continuous availability of constant sized MNB

V. CONCLUSION

The research conducted through this paper indicates that application of machine learning technology in the aspect of water treatment is feasible. Cost efficient methods such as decision trees can be a fruitful solution to handle binary aspect of any parameter list. Also stability in the result in terms of generation of the bubbles, correlation between experimental result to ML result has indicated that CART are effective solutions that can be applied for problems associated with continuous parameter analysis.

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AUTHORS PROFILE

Pinisetti Swami Sairam, is a research scholar and presently working as Research Scientist, University of Petroleum and Energy Studies. He comes with a background of B. Tech in Electronics and Communication Engineering and M. Tech in Robotics Engineering

Ravi Gunupuru is presently working as Assistant Professor in Dept. of Chemistry, University of Petroleum and Energy Studies, Dehradun. He has strong academic and research experience in the field of water treatment and nanoparticles.

Jitendra K Pandey is Associate Professors in University of Petroleum and Energy Studies. He has strong academic and research experience in the field of water treatment.