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Monitoring and Intelligible Alert System to control Water Quality in Reverse Osmosis Plants

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Abstract: ***The classification of drinking water quality severity from RO production plant needs appropriate methods to provide intelligible alert to the operators who involve to carry out remedial action in pace with the production. The proposed technique finds more relevance to detect instantly the quality variations in plant through efficient classification system and drives to reduce the cumbersome of operators. In this paper, it is proposed a SVM based classification method to detect drinking water quality attributes temporally and then precisely classifying severity condition in order to correct quality derivations. A different control scheme is experimented to detect quality variables like pH, TDS, ORP and EC and to support production system. Thus this contributes an automated diagnosis of water quality in RO plant. For classification, SVM is trained with data obtained around 8 plants from West and North of Chennai region. This is demonstrated specifically for a top-level classification job on Quality. On the features extracted from 1280 data, the SVM is trained and achieves a sensitivity of 85% and an accuracy of 90%***

Keywords : pH, Total Dissolved Solids (TDS), Oxidation-Reduction Potential (ORP), Electrical Conductivity (EC), Reverse Osmosis (RO), Support Vector Machines (SVM).

I. INTRODUCTION

Continuous monitoring of water quality in reverse osmosis (RO) plant and its classification to carry out remedial measures on processes are considered to be major problem of real-time production plant. Several RO plants though use instrument to measure water quality parameters need certain elaborate details to quickly carryout rapid remedial actions in real-time by the production supervisors or operators. Without these details, corrective actions may be delayed and operators may highly susceptible to commit errors in their actions. Using just the measurements of water quality that display by instruments, operators must earn skill to interpret them for corrective measures. Hence, water quality monitoring for real-time production need interpreted details rather than direct quality chemical parameters like pH, total dissolved salts (TDS), and oxidation-reduction potential (ORP).

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In recent days, significant steps were disseminated in the advancement of control and automatic monitoring approaches of water quality [1]. For the purpose, machine learning approaches are applied as an instrumental tool to support operator decision-making by observing more intelligible solutions that derived from crude technical data, recording monitoring variables straightaway from instruments. The basic thought is that these water quality data which are complex are to be transformed into the details of sensible and realistic to execute real-time corrective actions. This also makes simpler to deploy non-specialized individual for operation. Commonly the water quality linked to numerical specifications, a qualitative classification is recommended. Such qualitative based categorization allows the water quality corrective process in production easier and may be used in the learning process by artificial intelligence algorithms.

The major issues in automatic evaluation of potable water quality in production plant are the complication in measuring certain physical, chemical, and microbiological parameters in real-time, the use of skilled labor and the expense involved in obtaining those values. But a real-time supervision would contribute data continuously for any variations in production process are not neglected. It leads to the possibility to instantly identify variations in the conditions of water quality. The chief goal of the current analysis is to suggest a classification method of RO production plant water quality for intelligible data representation to carry out corrective actions if any quality variations in production just on the basis of real-time basic chemical parameters, particularly, the pH, TDS and ORP are chosen. The suggested approach that uses three essential chemical measurements must be potentially capable to predict intelligible information for the operator to make decisions to implement corrective measures concerning the water quality. RO plant across Chennai and other regions of North Tamil Nadu commonly use underground water from bore-well for treatment to control the water quality requirements in pH, TDS and ORP for drinking. The normal range of the underground water in mentioned regions: pH value is between 6.4 and 7.6, TDS range between 600-6500 mg/l, ORP range between 37 and 143 mV and EC range of 489-1561 S/cm [2, 3, 4, and 5]. The adjacent area in the mentioned regions has shown huge variations on parameters in their values [5]. The normal range of the drinking water recommended by WHO: pH value is between 6.4 and 7.6, TDS range between 300-500 mg/l, ORP range between 300 and 500 mV and EC range of minimum 400 S/cm [6].

II. RELATED WORKS

The present area of the research in the domain of water quality monitoring is attaining high accuracy to detect anomaly chemical characteristics of water and thereby correcting and controlling quality are difficult job.

A system of water quality real-time monitoring and anomaly detection on the basis of Multiclass Support Vector Machines (MSVM) is designed for production RO plant. This proposed system is practicable to provide intelligible information for operators to do decision-making and carry out effective corrective measures.

The model proposed by Yue &Ying [7] was constructed based on Wireless Sensor Network (WSN) powered by photovoltaic (PV) for a water quality monitoring system. The prototype was fabricated and realized using monitoring devices as nodes. Data sensed by several sensors involving pH, oxygen density and turbidity are transmitted to the base station. The proposed model had benefits of adaptable commissioning.

The technique suggested by Verma [8] was a water monitoring device to manage the pollution level. Monitoring, especially in India, water quality, significantly intensifies the degradation of water quality. His article contributed the demands and aptness of wireless sensor networks in water quality control. Being real time, constant and active sensing assistance by WSN, an early warning system can activate a suitable alert in adverse quality conditions.

'Smart Coast' devised by O' Flynn et al [9] applied a multi-sensor model for water quality management. It aimed to contribute an effective way to achieve the quality parameters as prescribed by Water Framework Directive (WFD). The important parameters involved were water level, turbidity, temperature, pH, conductivity, dissolved oxygen and phosphates. The designed WSN offered to achieve several flexible potentials.

The quality monitoring system constructed by Menon et al [10] used WSN for river water analysis. This model mostly included a signal characterizing, processing and radio link. The pH value that detected was sent to the base station via ZigBee applying signal conditioning and processing methods.

Using computer vision and computer based image processing technologies; Yuan et al [11] analyzed the fish school behavior in real time and predicted the water quality. The sensors measured the velocity of fish movement, rotational angle, three dimensional standard deviation and color of the body which represent fish behavioral variations. Long Short-Term Memory (LSTM) based deep learning neural network was applied to classify such fish parameters and predicted the water contamination.

The system developed by Jingmeng et al [12] used fuzzy algorithm based extensive assessment model and spatial clustering analysis in prediction of water quality on the basis of assessment variables as follows: Dissolved Oxygen, Nitrate Nitrogen, Ammonia Nitrogen, Total Nitrogen (TN), Total Phosphorus (TP), Total Carbon (TC) and Chemical Oxygen Demand (COD). The data gathered using different sensors were pre-processed and investigated using spatial cluster analysis technique.

A real-time monitoring device designed by Vijayakumar et al [13] used in prediction of water quality. It focused to contribute a sensor basis system that presents an IoT based architecture of cloud computation to allow the data of sensors accessible globally.

A water quality monitoring developed by Kedia [14] was applied to villages. It was a sensor-cloud dependent cost-effective scheme. It comprised sensor based embedded systems and concerned the difficulties and business including mobile network operators and the Government. This network system allows the Government openly to carry out proceedings on the basis of the severity of quality problems.

Real Time Water Quality Monitoring System developed by Bhatt and Patoliya [15] ensured to provide drinking water supply safely and the quality monitored in real-time using novel method of IOT (Internet of Things). The designed IoT comprised certain sensors which measured the water quality variables namely pH, turbidity, dissolved oxygen, conductivity and temperature. The sensed data were processed by micro-controller and such processed data were sent distantly to the main controller which was raspberry pi with Zigbee communication standards. Sensors data could be viewed ultimately on internet browser with the help of the cloud.

III. PROPOSED APPROACH

In recent days, significant attempts were employed in the advancement of automatic water quality monitoring and control approaches [16]. The machine learning methods are applied as an essential fundamental tool to support decision-making and provide a detailed solution by extracting them from raw data, generating straightaway from the monitoring data. Among several machine learning methods, Support Vector Machines (SVMs) found superior by its capability of training specifically larger dimensional data. SVM significantly and widely can be used for pattern recognition, density computation and regression [17]. Its convergence helps one to obtain a comprehensive optimum classification model with least complexity. SVM method is integrated to a proposed system to monitor the quality of drinking water and classify the water in operator viewpoint to carryout real-time corrective actions in production. The increasing challenge is observed as multiple classes based classification of water quality -highly alkaline, highly acidic, high TDS, high ORP, and low ORP as quality anomalies. The architecture of the monitoring and classification system, multi-sensors method, is depicted in Figure 1.

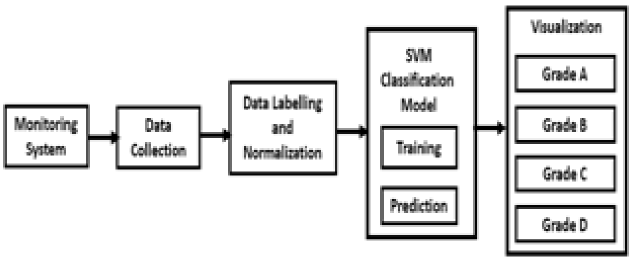

Fig. 1. Functional Diagram of Proposed System

In this section, the architectural concept on real-time monitoring of water quality in production environment. A comprehensive architecture of the suggested system is depicted in Figure 2. Each and block comprised in proposed system is described elaborately.

This proposed architecture consists several sensors like pH, TDS, ORP and Temperature are connected to main controller.

The main controller will accede the signals from the sensors and transfer them to PC for analysis. Arduino of ATMEGA 328p is utilized as a main controller.

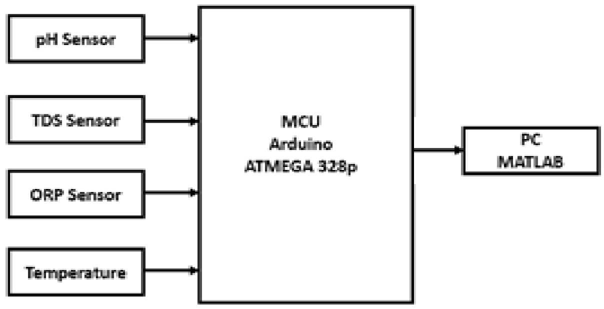

Fig. 2. Architectural block diagram of Monitoring System

A. pH sensor(SKU:SEN0161) [18]

A pH sensor is an electronic instrument which measures the pH level of any water based solutions as shown in figure 3. The pH value indicates the amount of the alkalinity or acidity feature of the solution. The pH value is obtained mathematically using logarithm and it ranges from 0 to 14 with a neutral value as 7. Values above 7 shows the solution is alkaline whereas the values less than 7 show acidity. The sensor works at a supply voltage of 5V and it is quite compatible with Arduino.

It comprises 3 different electrodes (i) Glass (ii) Reference and (iii) gel mixture. The pH is characterized as a negative logarithm value that indicates hydrogen ion concentration in a solution.

Fig. 3. pH sensor Probe

B. TDS Sensor (SEN0244) [19]

A TDS sensor specifies the total dissolved solids (TDS) present in the water based solution that is the concentration of dissolved solid particles as shown in figure 4. The presence of dissolved ionized solids, namely salts and minerals, will increase the electrical conductivity (EC) of a solution. Since it is volume based measurement of ionized solids, EC may also be utilized to evaluate TDS. EC will not substantially vary in the presence of dissolved organic solids, namely sugar and suspended organic colloids solution, and so they are ignored.

Fig. 4. TDS Sensor Probe

C. ORP sensor (AtlasEZO) [21]

The oxidation-reduction potential (ORP) measures the solution capacity to behave like oxidizing or reduction agent. It is used to measure the oxidizing capacity of chlorine in water or to find whether the neutral point equilibrium has been met in oxidization-reduction reaction. Chlorine in water treatment primarily used as disinfectant that is to destroy disease causing microorganisms like bacteria, viruses and protozoan which usually grow in water reservoirs, mains and storage tanks. Chlorine amounts up to 4 mg/l in water are deemed to be safer for drinking. Continuous exposure or drinking chlorine excess water may increase the risk of respiratory issues namely asthma particularly in children, tumor development in kidney and intestine and, cell and tissue damages [22].

D. Temperature Sensor (DS18B20) [23]

The water temperature changes based on the day-night conditions and climate. The water temperature is dependent on geographical position and season of environment. The normal drinking water temperature might be approximately between 7 and 44^{0}C. If uncommon chemicals added to the drinking water, it makes rise in temperature which exceeds the normality. The measurement range of DS18B20 temperature sensor will be nearly -55 to +125 °C.

E. Microcontroller (AtMEGA 328p UNO) [24]

Arduino, an open source platform commonly utilized for developing electronics applications. Arduino comprises components of both a physical programmable hardware which performs like microcontroller and software IDE (Integrated Development Environment) which runs on a computer and utilized for scripting and uploading C or C# code to the Arduino hardware. Several Arduino hardware are readily obtainable in market. For this project, AtMEGA328p UNO is selected in comparison with other types since it furnishes enough digital-analog IO pins for connecting several sensors simultaneously. AtMEGA 328p needs power supply of 5Vand operates at the clock rate of 16 MHZ. It can be connected to computer via universal serial bus (USB) and can store data up to 2 KB. It contains 14 digital I/O and 6 analog input pins. Four types of sensors are attached to 4 digital-analog IO pins of Arduino. Fig.6 depicts the Arduino UNO hardware that used.

F. Overview of SVM

The goal here uses Support Vector Machine (SVM) method applied to make decision on corrective action to rectify water quality in production RO plant. Support Vector Machine was initially presented by Vapnik et al in solving the problems in classification of patterns and regression.

SVM is a class of supervisory learning technique commonly applied for regression and classification [26]. It forms a part of a group of common linear classification. SVM, particular quality is concurrently reducing the error in classification error and increase the geometric margin. Thus SVM is also termed as Maximal Margin Classifier. SVM is regarded as Structural risk Minimization (SRM). It maps input vectors to a space of higher dimensions where a maximum partitioning hyperplane is built. Two hyperplanes of parallel are built on either sides of hyperplane that divide the data, refer Fig 5. The dividing hyperplane maximizes the space between such parallel hyperplanes. A supposition is formed in such a way if the margin or space between parallel hyperplanes is larger the error will be improved [26]. Consider the data in the form of $\{(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)$ in which, $y_n = 1$ or -1 a value indicating the class to of $x_n$size of sample. Every, x_n is a real vector with p dimensions. The downsizing is crucial to protect against attributes with large variance. The separating hyperplane, which is

$$\mathrm{w.x + b = 0} \quad (1)$$

In which b is constant and w is a vector of p dimensions. The w vectors are orthogonal to the dividing hyperplane. An addition of b permits to improve the margin, whereas in absence of it, the hyperplane is constrained to cross the origin, limiting the result. In order to maximize the margin, SVM and the hyperplanes of parallel are regarded. Hyperplanes are expressed

$$\mathrm{w.x + b = 1}$$
$$\mathrm{w.x + b = -1} \quad (2)$$

When the data for training are linear disjunctive, such hyperplanes are chosen such a way there exists no data between them and subsequently attempts to maximal the distance between them. The distance between hyperplane scan be determined as$2/|\mathrm{w}|$. Thus$|\mathrm{w}|$ has to be reduced to least. It is must to assure for all *i*

$$\mathrm{w.x}_i + \mathrm{b} \geq 1$$
$$\mathrm{w.x}_i + \mathrm{b} \leq -1 \quad (3)$$

By rearranging

$$y_i(\mathrm{w.x}_i + \mathrm{b}) \geq 1, 1 < i \leq n \quad (4)$$

SVM can be applied in two ways in applications: kernel technique and classifier with large margin. SVM is used for time series analysis, feature selection, chaotic system restoration and nonlinear principal component analysis.

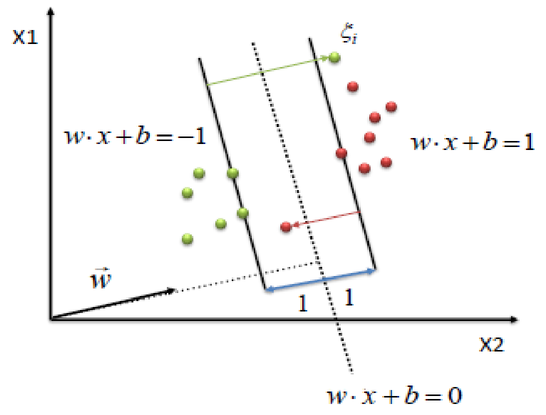

Fig 5. Hyperplanes of maximum margin for a SVM trained data from two classes [27]

G. *SVM Kernals*

The kernel is a function that translates the input data to a space with higher dimension in order to perform linear separation. This group of algorithms which applied for pattern detection, uses most popular component, the support vector machine (SVM). The input train vectors are translated to a space with higher dimensional using the function Φ. Thus SVM determines a dividing hyperplane on space with higher dimension with the maximum margin. The penalty variable C for error will be greater than 0.

There exist various types of SVM kernel functions. The option of a Kernel is influenced by the nature of issue that attempted to model. For example, a polynomial kernel will permit anyone to model attribute combinations to the extent of the polynomial order. Radial basis function (RBF) permits to choose circular distributed data on comparing with linear kernel, which this permits just to choose linear distribution.

Various kernel transforming functions exist. Those few are linear, normalized polynomial, RBF, Gaussian RBF, Sigmoid and String Kernels and so on. They are on the basis of need of uses. However the common kernels observed to operate excellent for broad range of applications are Linear, Polynomial and RBF.

IV. DATA AUGMENTATION

Presently, data of pH, TDS, ORP and Temperature were collected by random sampling technique that is 20 data at different random time in a day from randomly chosen 8 weeks in 6 months span such that visiting once in a week to 8 RO plants located in North Chennai and West Chennai suburbs and assembled into 4 arrays each of length 1280. Those collected data from 8 RO plants are depicted in graphs that shown in Fig. 6 for pH values, Fig. 7 for ORP values, Fig.8 for TDS values, Fig. 9 for EC values and Fig.10 for Temperature values.

From Table 1, following inferences can be deduced

- pH values recorded from different plants have shown that the water used for treatment are alkaline rather acidic
- ORP values recorded from different plants have shown that the water used for treatment are 95-105 mV which are less than recommended by WHO standards 300-500 mV.

- TDS values recorded from different plants have shown that the water used for treatment are well above between 990-1310 (mg/L) when compared to the WHO recommended values 300-600 mg/L.
- EC values recorded from different plants have shown that the water used for treatment are well above between 1100-1500 (µS/cm) when compared to the WHO recommended values less 400 µS/cm
- The proposed technique firmly evolved to classify the water quality conditions for corrective action in RO production plant on the basis of major appearances of quality anomalies like, high pH, high TDS and low ORP.
- Collecting data and grouping of water quality anomalies with respect to corrective action in pace with production are essential part for experiments.

For training the SVM and to classify the anomalies described in grades, the data of 1280 samples were recorded from 8 RO production plants around Chennai region of West and North. 160 data on different time and days were obtained from each RO plant. In order to decide the corrective action that to be carried out by plant operator to adhere the quality of water, the target classes are charted based on water quality anomalies as given in Table 2.

Fig 6. pH data recorded from RO plant at 8 locations, 4 from West Chennai sub-urban and 4 from North Chennai sub urban

Fig 7. ORP data recorded from RO plant at 8 locations, 4 from West Chennai sub-urban and 4 from North Chennai sub-urban

Fig 8. TDS data recorded from RO plant at 8 locations, 4 from West Chennai sub-urban and 4 from North Chennai sub-urban

Fig 9. EC data recorded from RO plant at 8 locations, 4 from West Chennai sub-urban and 4 from North Chennai sub-urban

Fig. 10. Temperature data recorded from RO plant at 8 locations, 4 from West Chennai sub-urban and 4 from North Chennai sub-uraban

TABLE 1 The minimum, maximum, mean, standard deviation (SD) and mean / SD values of recorded pH, ORP, TDS, EC and Temperature data

Parameter	Plant Id	Max	Min	Mean	Standard Deviation	Mean/SD In %
Ph	P1	7.7	7.2	7.49	0.151	2.02
	P2	7.82	7.22	7.53	0.164	2.18
	P3	7.85	7.27	7.57	0.156	2.06
	P4	7.86	7.28	7.56	0.150	1.98
	P5	7.62	7.05	7.31	0.139	1.9
	P6	7.65	7.06	7.35	0.144	1.96
	P7	7.68	7.09	7.39	0.151	2.04
	P8	7.75	7.15	7.42	0.157	2.12
ORP (mV)	P1	95.5	89.6	92.45	1.65	1.78
	P2	95.6	89.6	92.55	1.54	1.66
	P3	95.8	89.7	92.48	1.55	1.68
	P4	95.7	89.8	92.69	1.50	1.62
	P5	105.4	99.4	102.13	1.65	1.62
	P6	105.3	99.4	102.59	1.62	1.58
	P7	105.2	99.5	102.34	1.52	1.49
	P8	105.3	99.6	102.65	1.56	1.52
TDS (mg/L)	P1	1308	1200	1254.6	28.71	2.29
	P2	1302	1198	1250.8	29.74	2.38
	P3	1304	1199	1246.8	28.20	2.26
	P4	1306	1194	1251.4	29.06	2.32
	P5	1108	996	1051.4	30.47	2.9
	P6	1106	995	105.6	31.20	2.97
	P7	1108	998	1052.4	29.36	2.79
	P8	1102	996	1046.5	30.25	2.89
EC (µS/cm)	P1	1200	1100	1147.6	27.43	2.39
	P2	1208	1098	1146.7	28.66	2.5
	P3	1204	1098	1151.1	29.72	2.58
	P4	1202	1099	1150.9	29.37	2.55

	P5	1504	1396	1451.5	28.77	1.98
	P6	1502	1398	1449.9	27.22	1.88
	P7	1499	1395	1445.4	28.41	1.97
	P8	1502	1397	1448.3	29.83	2.06
Temperature (^{o}C)	P1	29.7	28.3	29.11	0.37	1.27
	P2	29.8	28.4	29.14	0.37	1.27
	P3	29.6	28.5	29.19	0.36	1.23
	P4	29.7	28.6	29.20	0.37	1.27
	P5	29.6	28.3	28.97	0.36	1.24
	P6	29.6	28.2	28.92	0.37	1.28
	P7	29.6	28.3	29.01	0.39	1.34
	P8	29.6	28.4	29.02	0.36	1.24

TABLE 2. Grading of Water Quality to monitor in RO production plant

Water Quality	pH	TDS	ORP	Corrective Action
Grade A	High	High	Low	Required
Grade B	High	Normal	Low	Required
Grade C	Normal	High	Normal	Required
Grade D	Normal	Normal	Normal	No need

V. EXPERIMENTS AND RESULTS

This section explains the experiment and the results obtained from SVM classifier by applying proposed classes as target described in Table 2.

Table 3 shows confusion matrix statistics of the classifier of SVM type and Fig 11 depicts the confusion matrix of the classifier while performing classification for water quality severity.

Fig 11. Confusion matrix of the SVM classifier when classifying the water quality severity

TABLE 3. Confusion matrix statistics of the classifier

Severity Classes / Parameters	Grade A	Grade B	Grade C	Grade D
Accuracy	89.84	86.71	93.75	99.22
Precision	79.13	66.23	97.92	100
Sensitivity	85.2	80.95	87.07	93.5
Specificity	94.05	88.61	98.65	100
F1	82.03	72.85	92.18	96.64

VI. CONCLUSION

The present analysis is carried out with a comprehension that effective grouping of water quality anomalies will likely to improve intelligibility for an operator to easily carry out corrective action to pace up with production. The classification here is a four class problem for overall detection of water quality severity of RO plant using a SVM classifier. The proposed method for classification has depicted positive indicators for obtaining the intelligible alert about water quality needed to rectify the severity, precisely treating the most imperative situations. So far, the previous researches were carried out to assess the water quality from water bodies or reservoirs. The present approach is aimed to analyze drinking water quality from RO plant that directly feeds the people. This method strongly establishes production control methods are very critical to improve drinking water quality.

The remarkable advantage of using direct measurements of water quality like TDS, pH and ORP for training the SVM classifier is that it allows the classifier to directly learn more of water quality attributes and provide intelligible alert for operators. For classification performance, the data that are used were identified and labelled through severity levels.

Practically, the data that supplied to SVM for grading water quality severity cannot precisely predict grades unless they are properly grouped into classes. The SVM has no problem of learning to identify potable water quality attributes since quite large volume of healthy attributes are available in the dataset. In order to classify the severity of extreme cases, the learning needed for training is substantially low. The problems arise when allowing the network to discern among slight severity variations

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