

A Survey of Existing Approaches for Water Pump Status Prediction

K. Karthik Prasad, Jayakrishna Bachu, E. Poovammal

Received 08 November 2018 • Revised: 30 November 2018 • Accepted: 06 December 2018

Abstract: Water Distribution Systems play an important role in shaping the quality of life of the public. However, we must realize that these systems are aging and have been deteriorated to the point that their service capabilities are now a matter of concern. Due to this fact there has been a growing awareness to improve the conditions of the water distribution system. The objective of the proposed system is to integrate the approaches followed by other systems to predict the functioning of a water pump by considering the various diverse factors that influence the water pump functioning such as water quality, source of the water, pressure on the system, age of the system, population density, various environmental factors, etc., and come up with a system that can predict the same with maximum efficiency.

INTRODUCTION

Water distribution system plays a vital role in the urban development and these pipeline systems have been laid and developed long time back. These systems have reached a point of deterioration often causing pipe burst leading to lot of social and economic stress. Water pipeline burst can be categorized as (1) structural deterioration and (2) functional deterioration.

Social and economic cost of pipe line failure is very expensive and very difficult to detect. Thus, raising need for strategy to solve the multi-objective problem. Most of the existing systems consider the factors that influence the distribution systems greatly, such as soil, water source, location, pressure on the system, etc and predict whether the system is in good condition, needs to be repaired or whether it is beyond repair and must be replaced completely.

For solving these problems, various evolutionary algorithms have been developed. Different mathematical simulations have been run on different load. Selection of exact algorithm for solving problem is difficult. Some algorithms may be better than other algorithms for a particular problem while at the same time could lead to a poor solution in other situations.

The system approach planned extends the present working systems with certain modifications which may lead to greater efficiency.

CURRENT TECHNIQUES

Deciding the Optimal Location to Set up the Representative Station

This system specifies methods to set up a representative station for the distribution system in an area depending upon certain factors. Setting up of a representative station is done as per the regulations specified by the U.S. Environmental Protection Agency that requires the water reaching the public to be safe for drinking which mandates all the drinking-water authorities to monitor the water quality in their distribution systems. The regulations ("Safe" 1974) prescribe the sampling frequency and the water-quality parameters to be monitored [1]. One catch is that the regulations do not specify how to set up the representative station.

K. Karthik Prasad, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, India. E-mail: karthikprasad887@gmail.com

Jayakrishna Bachu, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, India. E-mail: bachujaya1997@gmail.com

E. Poovammal, Department of Computer Science and Engineering, SRM Institute of Science and Technology, Chennai, India. E-mail: poovammal.e@ktr.srmuniv.ac.in

The system assumes that if a station is selected as the representative station and the quality of water is calculated at the station, then the quality of water at stations that are nearer to the representative station is known automatically. It also assumes that if the water quality at the representative station be determined, then the quality of water at stations that are upstream with respect to the representative station are similar to that at the representative station as the same water flows to the representative station.

The method to select to a representative station is given by: Each node is associated with a known demand. Thus, if the quality of water at a node i is known along with demand of the node i , i.e., d_i and the total demand D , then the fraction d_i/D of the total demand is known [1]. Then a cut-off percentage is determined above which a station can be considered as a representative station. Mathematically, the objective is to maximize the function given by equation 1:

$$\sum_{i=1}^n d_i y_i \tag{1}[1]$$

Figure 1 illustrates how the selection of the representative station is made. In the figure, node 5 is assumed to be the representative station and the fractional flow to every node is calculated where d indicates the demand and f_i indicates the flow of water through that station.

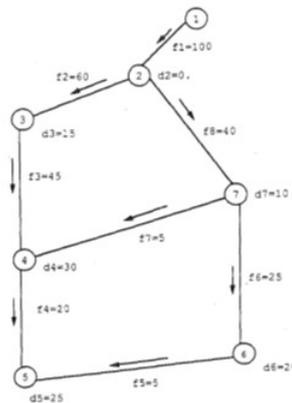


Figure 1: Water Distribution System

The mentioned system takes help from existing models such as the Kentucky Pipe Model and the WADSIO in order to determine the best location for a representative station. An addition to the system could have been to mention a solution to compare multiple sampling sites as there exists no quantitative measure to do the same.

Urban Water Quality Prediction

This system highlights the fact that predicting water quality in urban areas is more challenging than it sounds since the quality of water in an urban environment varies non-linearly and depends on various environmental factors such as meteorology, water-usage patterns, and land uses [2]. The entire system is built upon datasets of different domains such as meteorology, pipe networks, structure of road networks, etc., which are then combined using multi-task multi-view learning method.

The system consists of two components: multi-task learning and multi-view learning respectively and each component has a unique role. The multi-view learning tries to acquire two different views within a station while the multi-task learning acquires the relationships of the pipe networks among different stations. This method can help improve the predictive capability of all the stations [2].

The formula for the spatio-temporal multi-task multi-view learning is given by equation 2:

$$\min_{\mathbf{W}} \frac{1}{2} \sum_{l=1}^M \|y_l - \frac{1}{2} X_l w_l\|_2^2 + \lambda \sum_{l=1}^M \|X_l^s w_l^s - X_l^t w_l^t\|_2^2 + \gamma \sum_{l,m=1}^M C_{l,m} \|w_l - w_m\|_2^2 + \theta \|\mathbf{W}\|_{2,1}, \tag{2}[2]$$

where the first term is the loss function, the second term is the multi-view learning component, the third term is multi-task learning component and λ , γ and θ are regularization parameters.

Next, the system applies the multi-view learning to gather data from various domains and combines them into one single component which will be able to describe the properties of the object of study furthermore and thus enhance the results. The proposed system achieves a good success percentage by combing the data from various domains, but the system could have used a much simpler approach as the data needed should be in real-time and there is an increased cost factor due to installations of real-time monitoring systems.

Real-Time Water Quality Prediction

This system makes use of a hypothetical city A in which the model operates to determine the energy utilized by an old plant and a new plant and also the amount of pressure the entire distribution system experiences due to addition of new water sources. The system mainly focuses on the pipe network of the city A.

The first thing the system considers is the current age of the pipe network and the area they are serving. To proceed, the model utilizes two formulae given by the equations 3 and 4:

$$\sum Q_{in} - \sum Q_{out} = Q_{demand} \quad (3)[3]$$

$$H_i - H_j = H_f = \frac{4.73LQ^{4.73}}{C^{1.852}D^{4.87}} \quad (4)[3]$$

where equation 3 represents the Hazen-William equation used to derive a relationship between energy loss and pipe flow. Using the above equation, a hydraulic model was constructed and an analysis regarding the energy loss was carried out and certain benchmarks were set which the model had to satisfy, which by the way it did. A conclusion was drawn stating the constraints that the system had to manage to achieve the objective.

Prediction of Water Distribution System Based on Bayesian Distribution System

This study predicts any break in the pipeline network in water distribution system. It uses the Bayesian neural network for diagnostic and predictive management of water distribution system.

The system uses data such as average household age at census tract and population density of the area for determining the average age of the pipeline network. They took different samples of soil to determine its quality as well. They used United States Department of Agriculture National Resource Conservation Services (NRCS) soil data mart to capture the soil characteristics. [4]

Bayesian Neural Network (BNN) was learned using following learning algorithm: (i) Grow-shrink Algorithm

1. RsMax2 Algorithm
2. Gradient Decent Algorithm

Statistical learning may be hypothesis generating and might be less resourceful. Flexibility is required in both continuous data and discrete data. There is a need for improved discretization. Discrete observation may be a natural knowledge base for the BNN otherwise discretization of each variable has to justify and the interpretation of resultant BNN model.

Pipe Failure Methods in Water Distribution System

This system states that the water distribution system can break due to many reasons. Some of the reasons are: i) There is a single source of element and there is failure at any point in the pipeline. ii) Water demand is not met, this can be because of failure of booster pump.

The first type of failure is further classified into: a) failure in branch network and b) failure in a loop network. When a failure occurs in branch network, i.e., a network without any loops, then the water supply to the entire network is cut-off as the network is linear and the water has to pass through the entire network sequentially. However, when a failure occurs in a loop network, only a portion of the water supply is cut-off which increases the demand pressure on the remaining nodes due reduced water supply. In both the cases, if a short circuit occurs, i.e., if the water from the source finds a path to reach the last node without flowing through the network then the water supply to the network ceases.

The second type of failure is caused due excess demand in the network, restricting certain paths in the network due to maintenance and repair, or the failure maybe progressive. All in all, the pumps are made to work more than what they can handle due to which they fail which leads to the entire water supply being cut-off [5].

The formula for calculating the Micro Flow Distribution in performance assessment is given by the equation 5:

$$C_i = C_i^* \left[1 - a_i \exp \left(-b_i \frac{SP_i}{P_i^*} \right) \right] \quad (5)[5]$$

where C = nominal demand at a node, SP = service pressure at a node and a, b, P are constants.

The reliability estimation using Micro Flow Distribution is given by equation 6:

$$R = 1 - \sum_{ij} p_{ij} \quad (6)[5]$$

Uncertainty of Parameter Selection and Its Effects on Determining Water Quality

Monte Carlo simulations (MCS) was used to determine the effect on water quality due to uncertainty in selection of parameters. Advective transport and mass conservation at a node determines the water quality. Formula for conservation of mass for steady system at junction of two or more pipes is given by equation 7:

$$\sum_{l \in J_{in,i}} Q_l - \sum_{l \in J_{out,i}} Q_l = q_i \quad (7)[6]$$

$$\partial C / \partial t + V \partial C / \partial x = r(C) \quad (8)[6]$$

where dC/dx refers to rate of change of concentration in inflow to outflow, dC/dt refers to rate of change of constituent concentration of different elements and $r(C)$ refers to reaction relationship.

The reaction is due to decay that is mainly caused by a reaction between water and minerals of pipe and is given by equation 9:

$$r(C) = k(C - C^*)C^{nc-1} \quad (9)[6]$$

where k is the reaction constant and $k = k_b + k_{wall}$.

It was found that output uncertainty increased with input uncertainty by about 1.75 times and standard deviation increased by doubling the coefficient value of k_w . Due to bulk decay coefficient and global coefficient the output uncertainty increased faster than linear as coefficient values were increased [6].

Estimation of Leakage for Water Distribution System

The system proposes two methods for quantifying the water leaks in the water distribution system. First is the minimum night flow and second is the methodology of estimation of water leakage using advanced computational calculations.

Amount lost using minimum night flow method is calculated as mentioned in equation 10:

$$DRLV = F_{nd} \times Q_{mn} \quad (10)[7]$$

where DRLV refers to Daily Real Volume Loss, F_{nd} refers to night-day factor and Q_{mn}

refers to avg minimum night leak. F_{nd} is calculated by the sum of pressure acquired for 24 hours as shown in equation 11:

$$F_{nd} = \sum_{i=0}^{24} \left(\frac{P_i}{P_{3-4}} \right)^{N1} \quad (11)[7]$$

where P is the average pressure and P_{3-4} is the average pressure during 3-4pm.

In the second method epanet calibrator software is used for calibrating the water losses. Pressure data and observed flow are inserted into the software for calibration. The formula used for calibration is given by equation 12:

$$Q = C_e H^{N1} \quad (12)[7]$$

where N1 is 0.5 for metallic pipes, C_e is discharge coefficient and H is the nodal head.

This study suggested to use computational method for quantifying the water leakage in the distribution system [7].

Relationship between Pressure-Leakage of Some Failed Water Pipes

This study presented the data according to which the leakage exponent for corrosion holes was between 0.67 and 2.3, for round holes it was 0.5, for circumferential holes it was between 0.41 to 0.52 and for longitudinal cracks it was between 0.79 and 1.85.

In this study two ends of a broken water pipeline system were fitted with water distribution system and calibrated pressure system. Pressure transducer and flow meter reading was collected on a logger. Readings were taken after every 30 seconds. It was understood that flow and pressure included fluctuations in short term. The amplitude of fluctuations is low with low pressure and flow. This is caused due to effect of dampening on throttle valve.

It was observed that by using the asbestos cement pipes the distribution system failed. There were longitudinal cracks and the leakage component was much above 0.5. It was also observed that pipes which had parallel longitudinal crack had maximum leakage and diagonal cracks had minimum leakage.

It was also observed that with steel pipes higher the corrosion higher the exponent. Due to reduced supporting area because of corrosion, stress will increase thus causing increased pressure on the pipe. But for round hole pipe exponent is approximately equal to the theoretical value.

In case of longitudinal cracks exponent value is much higher than exponential value. With increase of length there was increase in exponent. For circumferential cracks the exponential value was much higher than the longitudinal stress due to the reason that circumferential stresses cracks elongates [8].

Water Distribution System with Both Distribution Leaks and Pressure Dependent Demands

This system proposes an efficient model to predict better results when new scenarios were run with the values of time period and coefficient related to the node. It is proposed that modulation of flow rate at nodes should be preserved.

Equation 13 is used for determining the total consumption at a node:

$$Q_{c,i} = Q_{d,i} + q_i \quad (13)[9]$$

where $Q_{c,i}$ refers to consumption at node i , $Q_{d,i}$ refers to demand at node i and q_i refers to quantity loss.

Leakage could be characterized using equation 14:

$$q_i = K_i (p_i - p_o)^\beta \quad (14)[9]$$

where p_i stands for pressure upstream, p_o stands for pressure downstream and K_i stands for orifice constant.

Finally, the demand can be determined using equation 15:

$$Q_{d,i}(k) = Q_{c,i}(k) - q_{1,i}(k) - q_{2,i}(k) \quad (15)[9]$$

Using the above different calculations an integrated water distribution system can be developed. In this paper the author has differentiated the leakage from modelled network and from non-modelled network. Parameters such as age of the pipe, total demand on them and average pressure at each node were considered [9].

Population Growth on Water Quality

In today's world, water pollution due to human activities is a major cause of concern and beyond a certain threshold limit, it poses a threat to the quality of water in the water body [10, 11]. A study shows that urban activities is one of the major causes for water pollution in the African and Asian countries [11]. Many studies that have been conducted to determine the amount of pollution mainly focus on the following parameters: i) biochemical oxygen demand (BOD), ii) dissolved nitrates-nitrogen ($\text{NO}_3\text{-N}$), iii) dissolved oxygen (DO), iv) soluble phosphorous ($\text{PO}_4\text{-P}$), v) total coliform (TC), vi) chlorophyll, and other substrates to base their conclusions [10, 11]. All the above parameters use the unit of parts per million (ppm) or milligram per liter (mg/L).

A study was conducted in Lake Victoria, Kenya to determine the amount of pollution due to human activities. A methodological way was followed wherein first, the physical examination of the area was carried out and the physical characteristics of the lake was determined such as the area of the lake, the

depth, its longitudinal and latitudinal positions, percentage of lake shared between the countries it falls in and also the population density range in those regions from a given year to the present. Next, the area around the lake was examined to find out the amount of wildlife the lake supported, the forest coverage, and the major industrial projects of which the lake was a part, such as, the hydroelectric project. In the final step, information about the environmental factors was collected, like rainfall, temperature ranges in a year and the terrain characteristics. Then, a sample of water from the lake was collected and sent to the Lake Victoria Environmental Management Project (LVEMP) laboratories for analysis. The data was then compared with the previous data acquired in a similar manner to estimate the amount of pollution caused. The results showed an increase in the level of NO₃-N and PO₄-P contents which increased the nutrient content of the lake due to increased surface runoffs which intern increased the amount of water hyacinth in the region which depleted the dissolved oxygen in the lake which posed a problem [10].

A similar study was conducted to determine the influence of population growth on the water quality of the Kelani River, Sri Lanka. The parameters considered were BOD, DO and TC. The study used a Bayesian Network classification approach to determine the appropriate range of population in a region around the waterbody for the water to be suitable for drinking and other domestic purposes. Next, actual data was collected at three points in the course of the river, i.e., at the two ends and in the middle section. The methods used for the analysis process was as specified by the Central Environmental Agency (CEA) of Sri Lanka and the quality control tests were as per the regulations of the American Water Works Association (AWWA), American Public Health Association (APHA) and the 2005 standards of the Water Environment Federation (WEF). The study then collected monthly data from the start of 2003 to the end of

2013 with some missing values due to technical and human errors [11]. The conclusion the study arrived at was like that of the study of Lake Victoria, Kenya, that the population in the regions surrounding the river kept rising due to which the nutrient content in the river also increased which made the water not fit for drinking purposes.

Water Quality Parameters for Domestic and Drinking Purposes

It is known that water covers around 70 percent of the Earth's surface and only a fraction of it can be used for human purposes. So, it is very essential to maintain the quality of the fresh water bodies which are very vulnerable, finite and play an important role in sustaining life. Scientists estimate that the total water on the Earth's surface contain physicochemical parameters such as, color, pH, BOD, chemical oxygen demand (COD), DO, total dissolved solids (TDS), turbidity, total suspended solids (TSS), and others, which make-up about 1.36 billion cubic kilometers of the total water content [12]. These parameters can be used to estimate the water quality of a water body. Table 1 illustrates some of the water quality parameters and their threshold limit as specified by the Indian Standard Specifications for Drinking Water, IS:10500.

Table 1: Water Quality Parameters

Parameter	Threshold Value (ppm or mg/L)
Colour	5
pH	6.5-8.5
Turbidity	10
Nitrates	45
Pesticides	Absent
Total Hardness	300
Copper	0.05
Chlorides	250
Fluorides	0.6-1.2
Mercury	0.001
Phenols	0.001
Sulphates	150
Cyanide	0.05
Residual Free Chlorine	0.2
Iron	0.3

Some of the other parameters include temperature which directly impacts the aquatic communities, conductivity which indicates the presence of free ions mainly due to increase in salinity, TSS which indicates the amount of erosion upstream from a particular place, TDS which indicates the amount of inorganic salts and dissolved materials in the water which mainly includes chemical compounds such as nitrates, calcium, magnesium, sodium, potassium, carbonates, chlorides, sulphates, etc., BOD which

indicates the amount of organic pollution to both surface water and waste, COD which is used along with BOD indicates the amount of organics in water, Ammonia Nitrogen which in high levels may harm the aquatic life by increasing the body pH or by altering the metabolism, Potassium which indicates the amount of fertilizers being used in an area as it directly relates to plant growth being one of the macro elements required by the plants, DO which indicates the amount of oxygen dissolved in water which is essential for sustaining life [12].

A study was conducted to estimate the water quality parameters of the Cauvery River in the Erode region, Tamil Nadu, India. Cauvery river originates in the foothills of the Western Ghats in Karnataka, India and flows for about 800 km before emptying into the Bay of Bengal. During its course, it flows through the Erode District in Tamil Nadu where the study was conducted. The study revealed the pH as 7.86, TSS as 690mg/L, TDS as 1004mg/L, total solids as 1580mg/L, total hardness as 340mg/L, chloride as 380mg/L, DO as 5.59mg/L, BOD as 38mg/L, COD as 304mg/L, phosphate as 6.0mg/L, electrical conductivity as 920S/cm, and sulphates as 60mg/L [13]. When the results of the study were compared with the IS:10500 standard, it can be observed that most of the water quality parameters were well beyond their prescribed limit which indicates the water was not fit for drinking purposes and had to be maintained better to make it fit for drinking and other domestic purposes.

PROPOSED SYSTEM AND TRAINING DATA

The proposed system is that of a simple linear Support Vector Machine (SVM) to model the given data and achieve the objective of predicting the status of the water pumps. The SVM was selected particularly because though it is a very simple model, it can easily model real world problems, performs well on dataset with many attributes and its functional form is very similar to that of the neural networks and most importantly it is cost effective. One speed breaker is that the SVM works only on numerical data, but the presented dataset has only character data due to which the dataset has to be first converted into a numerical dataset and all the empty values must be managed properly which otherwise will lead to faulty prediction. Since the dataset is quite large, the method of cross validation is applied wherein the training dataset is divided into two parts, one for training and the other for testing. Once the training and cross validation is done, a rough estimate can be drawn regarding the attributes to be used based on the percentage efficiency of the model. It also paves the way to many techniques that can be applied on the model to further improve the prediction efficiency.

If the above system fails to achieve the desired result then Artificial Neural Networks (ANN) will be employed to achieve the desired solution.

Figure 2 shows a part of the dataset the model must work on. The dataset nearly contains 41 attributes covering a wide variety of domains and nearly 59401 training values and 14851 test values.

#	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W					
39175	21959	0	Water	Water	1159	Water	37.26687	-5.38918	0	Pangani	Naronyo	Maryena	21	5	Kibeto	Kijungu	1	TRUE	GeoData	C/WVC	Water	box	TRUE					
39176	68110	0	Dive/angl	DWE/Angl	32.14354	0	0	0	0	Lake	Tang	Mtukala	Tabora	14	4	Urambo	Mzunganc	0	TRUE	GeoData	C/WVC		TRUE					
39177	50011	0	Governme	District	cor	37.6198	-3.13149	Kwa	Mains	0	Pangani	Kala	Kilimanjari	3	1	Rombo	Kisale	Msa	1	TRUE	GeoData	C Company	Kisale	Kital	TRUE			
39178	62447	0	World	WORL	vi	37.11964	-2.8624	Vibandani	0	Internal	Ilwashi	Arusha	2	6	Longido	Olmolog	200	TRUE	GeoData	C/WVC	Olmolog	u	TRUE					
39179	21256	500	Dit	DH	37.04359	-6.83134	Kwa	Muoli	0	Wari	/	Ru	Mtambara	Morogoro	5	1	Kilosa	Mabweret	140	TRUE	GeoData	C/WVC		TRUE				
39180	41133	0	Governme	Communit	36.94537	-3.23222	Josephat	0	Pangani	Loseiya	Arusha	2	7	Meru	Leguruki	130	TRUE	GeoData	C/WVC	Nasale	gra	TRUE						
39181	57438	0	Hesawa	DWE	31.48345	-3.52638	Kwa	Juma	0	Lake	Victo	Kierima	Kagera	18	2	Bakoba	Ru	Irindiya	0	TRUE	GeoData	C/WVC		TRUE				
39182	56853	0	Governme	CENTRAL	33.03877	-8.56358	Ruanda	Sh	0	Lake	Ruku	Lumbila	Ki	Mbeys	12	6	Msozi	Ruanda	0	TRUE	GeoData	C	Water	authority	TRUE			
39183	10154	0	1559	34.77679	-5.03166	Jumane	h	0	Internal	Mkurinko	Singda	13	2	Singda	Ru	Puma	1	TRUE	GeoData	C/WVC		TRUE						
39184	48325	0	TASAF	TASAF	36.15262	-6.00873	Ela	0	Wari	/	Ru	Vigango	Dodoma	1	4	Chamwinc	Chilionwa	0	TRUE	GeoData	C/WVC	Nosi	TRUE					
39185	40923	0	Songea	DWE	35.38055	-10.6563	Kwa	Mand	0	Ruvuma	/	Magima	Ki	Ruvuma	10	2	Songea	Ru	Lilambo	650	TRUE	GeoData	C/WVC		TRUE			
39186	62731	0	HOLLAND	HOLLAND	0	-2.00E-08	Amani	0	Lake	Victo	Nyamiric	Mwanza	17	1	Magu	Nkungulu	0	TRUE	GeoData	C/WUG			FALSE					
39187	48532	250	TWESA	TWESA	30.25502	-4.63489	Zaharoti	0	Lake	Tang	Nyamiric	Kigoma	16	2	Katubi	Rungwe	M	450	TRUE	GeoData	C	Water	suit	TWESA	TRUE			
39188	72939	0	Kivanda	Artisan	39.4124	-8.75533	Hospital	Ki	0	Ruvuma	/	Kijini	Lindi	80	13	Kilwa	Kranje	Siq	1	TRUE	GeoData	Consillants	Ltd		TRUE			
39189	8941	1500	Mision	DWE	35.73499	-10.8184	Kwa	Chark	0	Ruvuma	/	Mzungano	Ruvuma	10	2	Songea	Ru	Medimira	0	TRUE	GeoData	C/WVC	Mradi	wari	TRUE			
39190	64242	0	0	33.89437	-9.39049	Kiloba	0	Lake	Nyos	Kiloba	Mbeys	12	4	Rungwe	Kisege	0	TRUE	GeoData	C	Water	suit	K	TRUE					
39191	62177	0	Dwsp	DWE	0	-2.00E-08	Wazaco	0	Lake	Victo	Mwamabi	Shinyanga	17	1	Baniadi	Mtanzu	0	TRUE	GeoData	C/WUG			FALSE					
39192	18354	0	961	35.93181	-3.63251	Zaharoti	0	Internal	Ottokay	Arusha	2	1	Monduli	Esilalei	1	FALSE	GeoData	C	Parastatal			FALSE						
39193	42641	500	Kikt	Wllagers	34.8961	-8.50206	Kwa	Fedo	0	Rufiji	Mkolongo	Iringa	11	4	Njombe	Mokombal	250	TRUE	GeoData	C/WVC			FALSE					
39194	15982	2500	Shipo	Shipo	34.73431	-8.8996	Kwa	Ignasi	0	Rufiji	Igalali	Iringa	11	4	Njombe	Mtwango	35	TRUE	GeoData	C/WVC	Mtikanga		TRUE					
39195	60832	0	Vifafi	1184	VIFAI	34.06752	-1.63724	Shulemi	0	Lake	Victo	Burundi	Mara	20	3	Musoma	R	Bainegi	827	TRUE	GeoData	C	Parastatal		FALSE			
39196	50585	0	Songea	MWE	1040	MWE	35.67013	-10.5094	Shule	Ya	K	0	Lake	Nyos	Tanga	Ruvuma	10	4	Songea	Ru	Tanga	2500	FALSE	GeoData	C	Other		FALSE
39197	48133	20	Private	Inc	288	WU	38.40797	-6.11938	Mtami	0	Wari	/	Ru	Kipera	A	Pwani	6	1	Bagamoye	Miono	80	FALSE	GeoData	C	WUA	Chalize	u	TRUE
39198	48076	300	Germany	F	1341	CES	37.20122	-3.22578	Kwa	Zabur	0	Pangani	Bwani	Kilimanjari	3	5	Hoi	Mochame	75	TRUE	GeoData	C	Water	Box	Uroki	Bori	TRUE	
39199	20973	25	0	46	39.09168	-6.63936	Saidi	Mwa	0	Wari	/	Ru	Nape	Dar	es	Salis	7	1	Kinondoni	Bunju	162	TRUE	GeoData	C/WVC		FALSE		
39200	4615	0	Dino	Dino	1307	Dino	34.28743	-1.6967	Dino	Sipla	0	Lake	Victo	Kibaboi	Mara	20	2	Serengeti	Kenyanon	160	TRUE	GeoData	C	Other		TRUE		
39201	65468	0	TASAF	TASAF	37.92801	-4.18412	Kwa	Mueli	0	Pangani	Mbakweni	Kilimanjari	3	3	Same	Mtindo	110	TRUE	GeoData	C	Water	suit	Mbakweni	TRUE				
39202	20017	0	Anref	Anref	40.16081	-10.5784	Kwa	Rashi	0	Ruvuma	/	Misi	Mtwara	99	1	Mtwara	Ru	Chawi	250	TRUE	GeoData	C/WVC	Ngonje	wo	TRUE			
39203	44780	0	FINN	WAT	37.88856	-9.87409	Kwa	Mzee	0	Ruvuma	/	Simba	Jum	Lindi	80	43	Liwale	Milimo	250	TRUE	GeoData	C/WVC		TRUE				

Figure 2: Part of the Training Data Set

RESULTS AND DISCUSSION

After applying the simple linear SVM on the dataset, a percentage success of 58.41 was achieved. Next K- Nearest Neighbor algorithm was applied on the same dataset and a percent-age success of 70 was achieved. Finally, K-means Clustering technique was used and it resulted in a percentage success of mere 41.81. Figure 3 and 4 shows the comparison between the three different approaches on the same dataset.

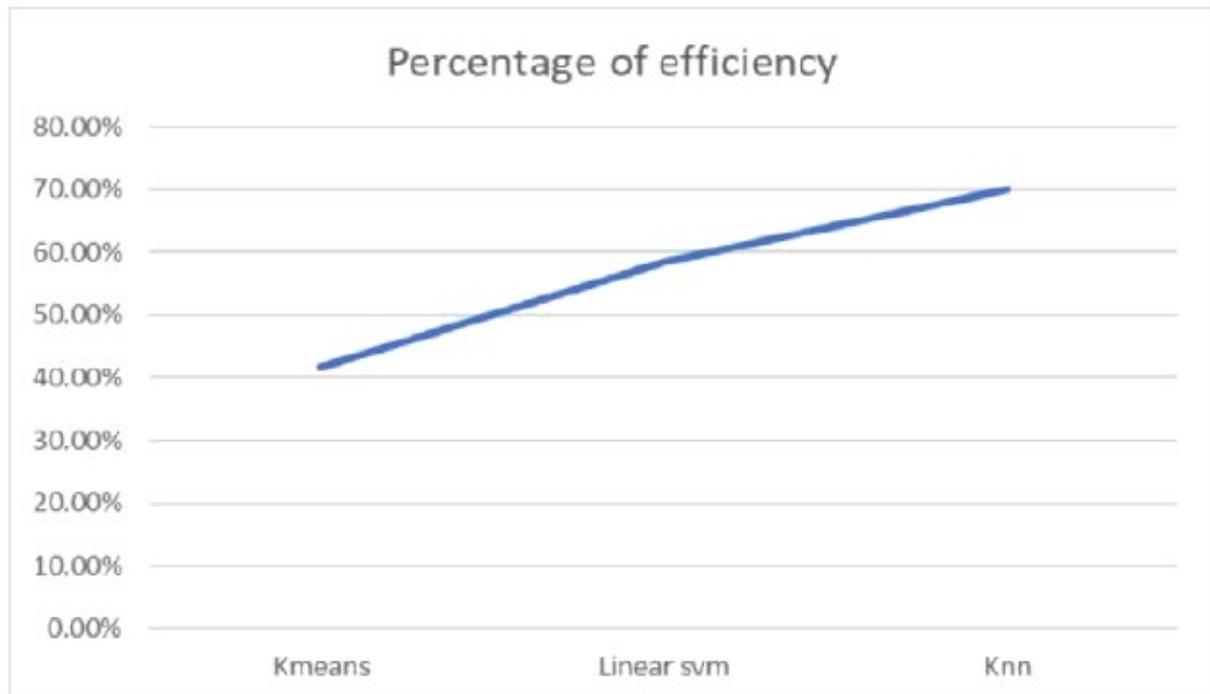


Figure 3: Line Graph Determining the Percentage Efficiency

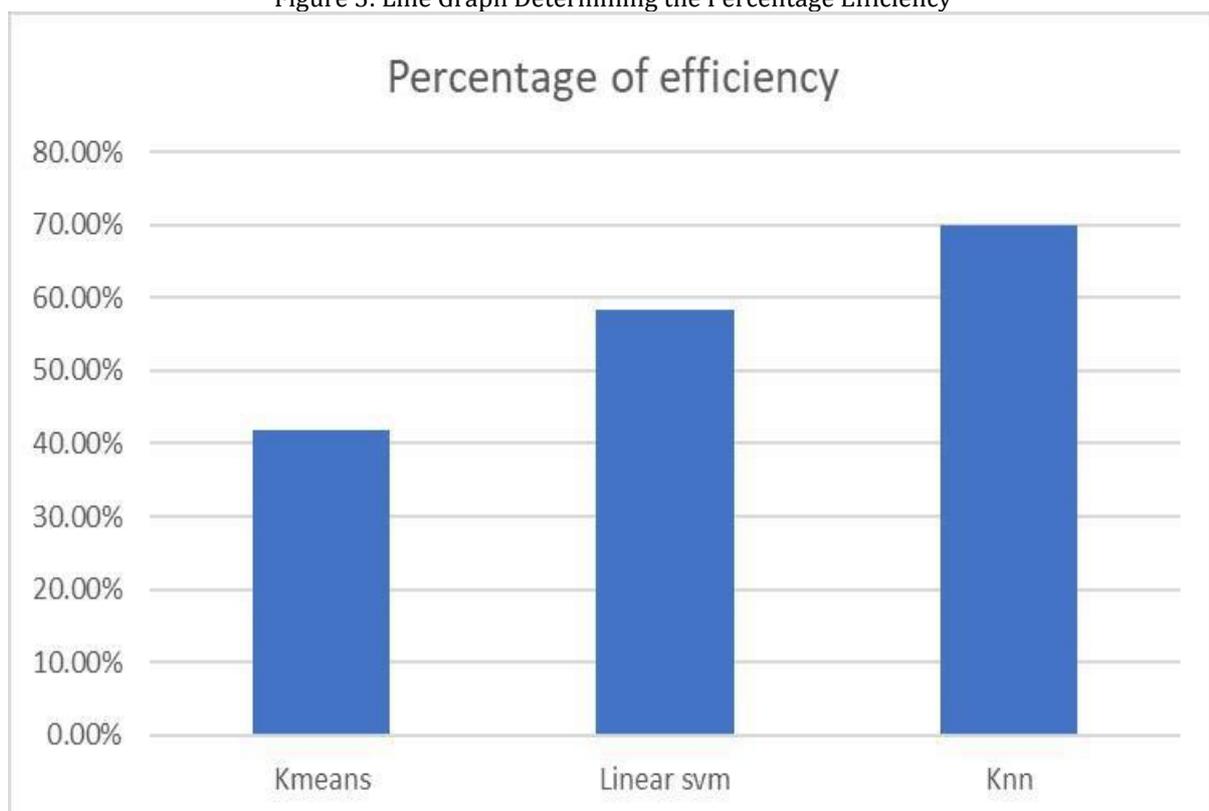


Figure 4: Line Graph Determining the Percentage Efficiency

Figures 5, 6 and 7 show the dataset after converting the character data to numerical data and cleaning, i.e., only keeping the attributes necessary for the prediction process.

```

status_group amount_tsh subvillage region region_code population \
0 1 6000.0 18176 10 11 109
1 1 0.0 7080 19 20 280
2 1 25.0 13380 2 21 250
3 0 0.0 2370 6 90 58
4 1 0.0 14540 20 1 18

permit construction_year extraction_type extraction_type_group \
0 0.0 1999 3 1
1 1.0 2010 3 1
2 1.0 2009 3 1
3 1.0 1986 13 10
4 1.0 0 3 1

management water_quality quality_group quantity source \
0 7 7 5 3 3
1 9 7 5 0 5
2 7 7 5 3 0
3 7 7 5 1 7
4 4 7 5 4 5

waterpoint_type source_class
0 2 0
1 2 2
2 5 2
3 5 0
4 2 2

status_group amount_tsh subvillage region region_code \
count 59400.000000 59400.000000 59400.000000 59400.000000 59400.000000

```

IPython console History log

Figure 5: Converted Database 1

```

count status_group amount_tsh subvillage region region_code \
mean 0.688434 317.650385 9571.109310 10.425017 15.297003
std 0.599877 2997.574558 5570.905689 5.965701 17.587406
min 0.000000 0.000000 0.000000 0.000000 1.000000
25% 0.000000 0.000000 4741.000000 5.000000 5.000000
50% 1.000000 0.000000 9537.500000 10.000000 12.000000
75% 1.000000 20.000000 14358.000000 16.000000 17.000000
max 2.000000 35000.000000 19287.000000 20.000000 99.000000

count population permit construction_year extraction_type \
mean 179.909983 0.654074 1300.652475 6.429259
std 471.482176 0.475673 951.620547 4.213783
min 0.000000 0.000000 0.000000 0.000000
25% 0.000000 0.000000 0.000000 3.000000
50% 25.000000 1.000000 1986.000000 5.000000
75% 215.000000 1.000000 2004.000000 8.000000
max 30500.000000 1.000000 2013.000000 17.000000

count extraction_type_group management water_quality quality_group \
mean 4.106263 6.556700 6.169411 4.423316
std 3.784239 2.159014 2.114989 1.497714
min 0.000000 0.000000 0.000000 0.000000
25% 1.000000 7.000000 7.000000 5.000000
50% 2.000000 7.000000 7.000000 5.000000
75% 6.000000 7.000000 7.000000 5.000000
max 12.000000 11.000000 7.000000 5.000000

count quantity source waterpoint_type source_class
count 59400.000000 59400.000000 59400.000000 59400.000000

```

IPython console History log

Figure 6: Converted Database 2

	quantity	source	waterpoint_type	source_class
count	59400.000000	59400.000000	59400.000000	59400.000000
mean	2.080505	4.25096	3.583754	0.453434
std	1.396032	2.99683	1.804421	0.834624
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	1.000000	2.000000	0.000000
50%	3.000000	3.000000	3.000000	0.000000
75%	3.000000	7.000000	6.000000	0.000000
max	4.000000	9.000000	6.000000	2.000000
[0 0 1 ..., 1 0 1]				
[[5270 2013 175]				
[1957 8400 362]				
[432 664 329]]				
	precision	recall	f1-score	support
0	0.69	0.71	0.70	7458
1	0.76	0.78	0.77	10719
2	0.38	0.23	0.29	1425
avg / total	0.70	0.71	0.71	19602

Figure 7: Converted Database 3

To improve the efficiency further, the method of information gain is suggested and is being applied on the model currently.

REFERENCES

- [1] Lee B.H and Deininger R.A 1992 Jan Optimal locations of monitoring stations in water distribution system *Journal of Environmental Engineering* **118(1)** 4-16
- [2] Liu Y, Liang Y, Liu S, Rosenblum D.S and Zheng Y 2016 Oct 29 Predicting urban water quality with ubiquitous data *arXiv preprint arXiv:1610.09462*
- [3] Shihu S, Dong Z, Suiqing L, Mingqun M, Ming Z, Yixing Y, Jinliang G and Hongbin Z 2010 May 7 Decision support system of water distribution network expansion *2010 International Conference on E- Business and E-Government. IEEE* (pp. 1520-23)
- [4] Francis R.A, Guikema S.D and Henneman L 2014 Oct 1 Bayesian belief networks for predicting drinking water distribution system pipe breaks *Reliability Engineering & System Safety* **130**, 1-11.
- [5] Jowitt P.W and Xu C 1993 Jan Predicting pipe failure effects in water distribution networks *Journal of Water Resources Planning and Management* **119(1)** 18-31
- [6] Pasha M.F and Lansey K 2010 Jan 1 Effect of parameter uncertainty on water quality predictions in distribution systems-case study *Journal of hydro informatics* **12(1)** 1-21
- [7] Cheung P.B, Girol G.V, Abe N and Propato M 2010 Night flow analysis and modeling for leakage estimation in a water distribution system *Integrating water systems* 509-13
- [8] Greyvenstein B and Van Zyl J.E 2007 Mar 1 An experimental investigation into the pressure-leakage relationship of some failed water pipes *Journal of Water Supply: Research and Technology-AQUA* **56(2)** 117-24
- [9] Martinez F, Conejos P and Vercher J 1999 Developing an integrated model for water distribution systems considering both distributed leakage and pressure-dependent demands *In WRPMD'99: Preparing for the 21st Century* (pp. 1-14)
- [10] Juma D.W, Wang H and Li F 2014 Apr 1 Impacts of population growth and economic development on water quality of a lake: case study of Lake Victoria Kenya water *Environmental Science and Pollution Research* **21(8)** 5737-46
- [11] Liyanage C and Yamada K 2017 Aug Impact of population growth on the water quality of natural water bodies *Sustainability* **9(8)** 1405
- [12] Tiwari S 2015 Water quality parameters-A review *International Journal of Engineering Science*

Invention Research & Development **1(9)** 319-24

- [13] Appavu A, Thangavelu S, Muthukannan S, Jesudoss JS and Pandi B 2016 Study of water quality parameters of cauvery river water in erode region *Journal of Global Biosciences* **5(9)** 4556-67
- [14] Vishwakarma S, Varma A and Saxena G 2013 Apr 30 Assessment of water quality of Betwa River, Madhya Pradesh, India *International Journal of Water Resources and Environmental Engineering* **5(4)** 117-222