Machine Learning – Based Detection of Water Contamination in Water Distribution Systems

Hadi Mohammed[1], Ibrahim A. Hameed[2], Razak Seidu[1]

[1] Water and Environmental Engineering Group, Department of Marine Operations and Civil Engineering, Faculty of Engineering

[2] Department of ICT and Natural Sciences, Faculty of Information Technology and Electrical Engineering

Norwegian University of Science and Technology (NTNU)

Postboks 1517, NO-6025 Ålesund, Norway

{hadi.mohammed, ibib, rase}@ntnu.no

Abstract - Accurate detection of natural or intentional contamination events in water distribution pipes is critical to drinking water safety. Efficient early warning systems that can detect contamination events require detection algorithms that can accurately predict the occurrence of such events. This paper presents the development of adaptive neuro-fuzzy inference system (ANFIS) models for detecting the safety condition of water in pipe networks when concentrations of water quality variables in the pipes exceed their maximum thresholds. The event detection is based on time series data composed of pH, turbidity, color and bacteria count measured at the effluent of a drinking water utility and nine different locations of sensors in the distribution network in the city of Ålesund, Norway. The proposed ANFIS models correctly detected between 92% and 96% of the safety condition of the water in the pipe network, with approximately 1% false alarm rate during the testing stage. The models also achieved high rates of specificity and precision, with very high correlations between the predictions and actual conditions of the water in the pipes. The accuracy of the models achieved in this study suggests that the models can be useful in real time contamination event detection in the pipe networks.

Keywords: Water safety, distribution network, contaminant detection, machine-learning algorithms.

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I. INTRODUCTION

Water distribution systems are vulnerable to further contamination of treated water as a result of physical or hydraulic breaches such as cross-contamination, breakages in pipes, wastewater intrusion and water quality integrity. Pathogens can enter such deficient pipe networks through backflow from cross-connections and from leaks and cracks [1]. This mode of contamination of drinking water is one of the main causes of poor public health worldwide. Even when treatment plant effluent is compliant with drinking water quality regulations, malfunctioning in water distribution networks can lead to increased gastrointestinal illnesses (GII), and potentially a health risk to consumers of tap water [2]. Deficiencies in distribution systems are therefore identified as potential risk factors for intermittent GII incidences in microbial risk assessment models [3].

The WHO estimates that 62 million people in Europe live in houses without direct water supply, and as a result of unsafe drinking water and poor hygiene and sanitation, an average of 10 deaths per day from diarrhea are assumed to occur in this region [4]. Despite great improvement in water supply systems in Norway over the recent years, there is still a risk of water contamination before reaching the consumer. Further, not only do fractures and leakages increase the risk of GII in the country, but also the re-contamination of drinking water is likely to increase in future as a result of vulnerabilities in aging pipelines [5]. The provision of safe drinking water to the public is vital for ensuring the welfare of the society, therefore, development of early warning systems (EWS) for detecting and/or predicting contamination events in water distribution pipes is an active area of research in recent times. Water quality motoring sensors are usually placed at different locations in distribution networks to provide real time changes in the quality of treated water. The optimal placement of these sensors in the pipe networks necessary for efficient coverage have been widely investigated by researchers [6]. The accuracy in the detection of contamination events from either natural or intentional causes is also vital to the security of water supply systems. However, few studies have explored the analysis of the measurements from these sensors and their ability to detect critical changes in the quality of water that are necessary for developing EWS.

Such EWS composed of online sensors, connected supervisory control and data acquisition (SCADA), detecting algorithms, and decision support systems [7], can mitigate the health risks associated with contaminations in water distribution systems when efficiently installed. In EWS, the detecting algorithm used can be critical to the accuracy of detecting contamination events and distinguishing them from normal fluctuations in the water quality parameters [8]. One approach to such event detection is to use data-driven techniques to evaluate the data measured by the online sensors [9]. For instance, Klise and McKenna, 2006 [10] applied multivariate Euclidean Distance (MED) method to classify new sets of water quality data from sensors as normal or anomalous. In a related study, McKenna et al. in 2008 [8] compared the performances of three water quality change detection algorithms at four different locations in the US. The three methods they applied were; linear prediction filters (LPF), in which a current value is predicted as a linear combination of previous samples, MED method, which involves comparison of two successive distances in a multivariate space defined by the water quality signals, and time series increments methods. The approach involved spiking each data set with simulated water quality values. Other researchers have applied supervised learning techniques including artificial neural network (ANN) and support vector machine (SVM) to distinguish anomalous water quality values from normal values, as well as evaluate potential quality threats in water distribution systems [11, 12]. Although these artificial intelligence methods are highly efficient, they are opaque, and therefore difficult to understand and interpret, particularly when the results are used for making far-reaching decisions.

The objectives of this study are 1) Apply Pearson's correlation analysis on the water quality time series to evaluate the effects of variations in the water quality parameters on the safety condition of water in the distribution network. 2) Use adaptive neuro-fuzzy inference system (ANFIS) model to detect deviations of water quality from baseline values established in Norwegian water safety regulations. An efficiently trained and tested model of this nature could be linked with the online water quality sensors in the distribution networks such that outputs will be obtained from routinely measured parameters in the pipes. The ANFIS approach applied in this study is aimed at overcoming the limitations present in other machine-learning techniques that have been used in contamination event detection in water distribution systems. In this method, fuzzy relations among water quality variables measured from the sensors detect contamination events. This technique offers a means of understanding the effects of each water quality variable on the overall safety condition of the water.

II. METHODOLOGY

A. Study Area and Data Set

Fig. 1 shows the map of study area and the locations of the Ålesund water treatment plant (WTP) as well as the various sampling points across the water distribution network, where water quality parameters used in this study were measured. The WTP draws water from the Brusdalsvatnet Lake located on the inland of Oksenøya in the Møre and Romsdal County between the Ålesund and Skodje municipalities in the West Coast of Norway. The lake has a surface area of approximately 7.1 km^2, with a mountainous and heavily forested catchment area of approximately 30 km^2. The Lake is the main source of drinking water for the nearly 50 000 inhabitants of the city of Ålesund and neighboring Sula municipality. The drinking water treatment facility draws 55,000 m^3 of water daily from the Lake at a depth of 35m. The data used in this study consist of monthly measurements at the outlet of the WTP and the various sampling locations in the distribution pipes. The data, which were taken from January 2013 to June 2017, were composed of water pH, turbidity (NTU), color (mg Pt/l) and counts of total bacteria (counts/ml) in the clean water. To obtain enough data for training and testing the models, we merged the data from all the locations to constitute 504 data samples.

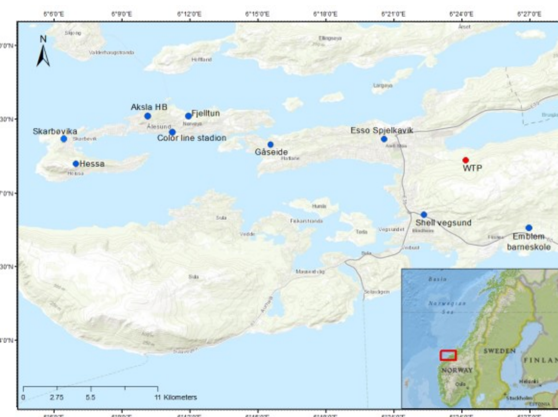

Fig. 1. Map of study site showing the locations of the distribution network where water quality parameters were measured.

B. Descriptive Statistics of Data

Prior to the model development, Pearson correlation coefficients (r) among measured water quality parameters from the effluent of the treatment plant and the measured parameters from the sensors located in the pipes were calculated as follows:

$$r_{XY} = \frac{\sum_{i=1}^{n}(x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{X})^2} * \sqrt{\sum_{i=1}^{n}(y_i - \bar{Y})^2}} \tag{1}$$

where X and Y are the measured values for two different water quality parameters in the treatment plant effluent and the distribution pipe respectively x_i and y_i are the i^{th} values in the time series, n is the number of data points used to calculate the correlations, and $\bar{X}$ and $\bar{Y}$ refer to the mathematical expectation.

C. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS), proposed by Jang (1993) [13], is based on the first-order Sugeno fuzzy model. By analyzing mapping relationships between input and output data, ANFIS optimizes the distribution of membership functions by using a back-propagation gradient descent algorithm either alone or combined with a least-squares method [14]. The technique has been widely used to model water quality indices [15, 16]. The objective of the ANFIS models in this study was to classify the water samples in the distribution pipes as “safe” or “unsafe”. The safety condition of the water samples were initially determined using domain expert information. In this study, two ANFIS models were built, one with a triangular objective function and the other with a Gaussian function. The proposed ANFIS has four inputs; pH, turbidity, color and bacteria count, and two outputs, the safety condition of water in the distribution pipes. Three membership functions were assigned to each input variable, resulting in 81 fuzzy rules for the four input variables. Each input is represented by three fuzzy sets and the output by a first-order polynomial of the inputs. The ANFIS extracts *n* rules mapping the inputs to the output from the input/output dataset. A typical Sugeno-fuzzy rule can be expressed in the following form:

$$\begin{aligned} &\mathrm{R_i\ IF\ pH\ is\ A_{1,j}} \\ &\mathrm{AND\ Turbidity\ is\ A_{1,j}} \\ &\vdots \\ &\mathrm{AND\ Color\ is\ A_{m,j}} \\ &\mathrm{THEN\ Safety_i} = \mathrm{f_i(pH, Turbidity, \ldots, bacteria\ count)} \end{aligned} \tag{2}$$

where $A_{1,j}$, $A_{2,j}$, …, $A_{m,j}$ are fuzzy sets or fuzzy labels used to fuzzify each input, $Safety_i$ (i.e., safety condition of rule *i*) is either safe or unsafe.

Figure 2 shows the structure of the five-layered ANFIS model built in this study. The first layer is the fuzzification layer, where all inputs are fuzzified. The degrees of membership of each input is calculated using either a triangular membership function or a Gaussian function. Layer 2 is the rule layer, where the membership functions are multiplied at each node to produce the firing strength of each rule. In the third layer, the value at each node is calculated as a ratio of the firing strength of the i^{th} rule to the sum of the rule’s firing strengths. Each node in layer 4 as adaptive, and contains a node function, and layer 5 is a single fixed node that calculates the overall output as a summation of all the incoming signals.

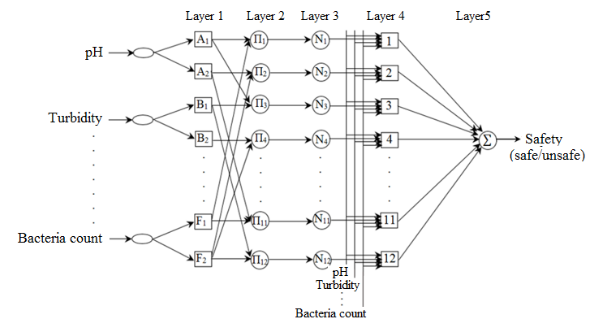

Fig.1. ANFIS architecture for first order Sugeno fuzzy model as used in this study.

D. ANFIS Model Development

To classify the measured data points as safe of unsafe, we used values from the Norwegian Guide to Drinking Water Regulations [17]. According to this regulation, concentration of total bacteria in the treated water should not exceed 100 CFU/ml, and there should be no irregular variations in the concentration for a given period. Moreover, the acceptable range of water pH is 6.5 – 9.5, while turbidity and color have no specific thresholds, although no irregular variations should occur. Nonetheless, the Norwegian Food Safety Authority recommends that for water supply systems that rely on surface water bodies, the turbidity of the treated water should not exceed 1 NTU. Similar regulations exist for color, with the maximum threshold set to 20 mg Pt/l. When the threshold values for total bacteria, pH, turbidity and color were used to sort the data in this study, 13 data points were classified as unsafe, out of the 504 samples. In order to obtain enough data points for training an efficient model, we tightened the values in these regulations, with thresholds of 80 CFU/ml and 6.5 – 9 for total bacteria and water pH respectively.

This resulted in a total of 89 samples found unsafe and the rest 504-89= 415 found safe. To have a dataset which equally and fairly represents the two cases, 89 sample taken from the 415 samples that are safe in random. Thus, there were 89 samples of safe water and 89 samples of unsafe water. Finally, all safe data points were assigned (+1) whereas all unsafe points were labelled (-1). The resulting data set was normalized using principal component analysis (PCA). The normalized data set was randomly partitioned into two; 70 % for mode training and 30 % for testing. The random partitioning was carried out to ensure equal representation of the variabilities in the water quality for both training and testing sets such that genuine assessment of the predictive ability of the model can be assessed during testing. Two ANFIS models were trained using the data set, one with Gaussian Membership functions (MFs) and the other with Triangle Membership functions.

III. RESULTS

A. Results of Descriptive Statistics

The distributions of the four water quality variables in the pipes between January 2013 and October 2017 are shown in Fig. 3 (a). High variabilities exist in the data generally, but this variability is less pronounced in the water pH. The count of bacteria, turbidity, and color are highly skewed, although the values mostly fall below their respective maximum thresholds in the drinking water safety standards of Norway. Fig. 3 (b) shows the results of the Pearson's correlation coefficients among the water quality variables in the pipes.

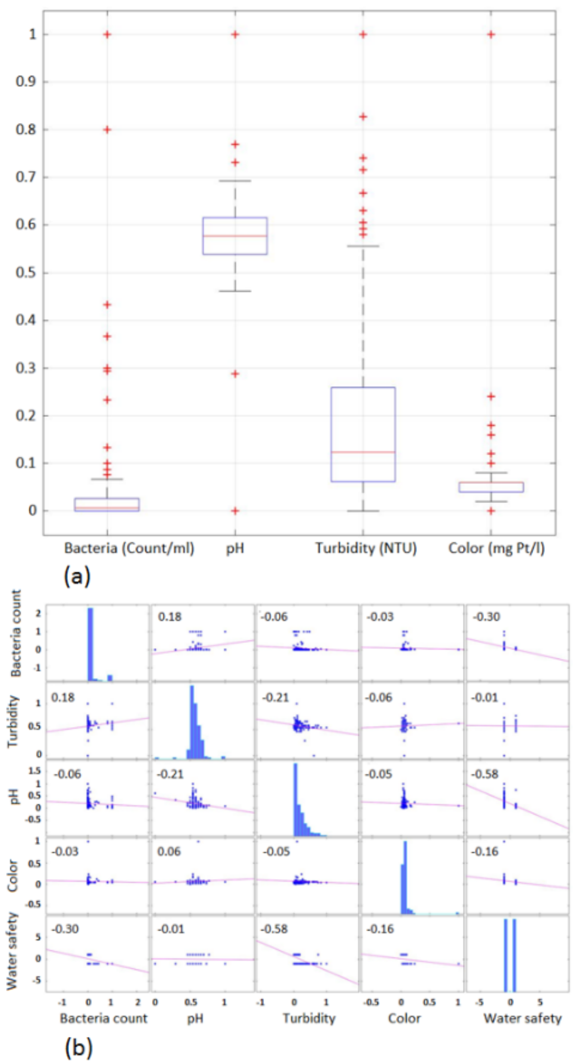

Fig. 2. Boxplots of raw data set (a) and Pearson's correlation matrix of water quality variables in the distribution pipes.

The safety condition of the water in the pipes was also included as a dummy variable, and overall, this condition was negatively correlated with all the parameters. The magnitudes of these correlations were higher with respect to the bacteria count (r = -0.30) and turbidity (r = -0.58). This was partly due the use of the bacteria count as the key determinant of the safety of the water. Values of turbidity and color measured in the pipe networks over the study period were much lower than the threshold values indicated in the regulations. Thus, it was it was not possible to use the water turbidity to classify the water in terms of safety. However, turbidity showed the strongest negative correlation with the safety condition of the water. This may be due to its positive association with the count of bacteria in the water, as it was the only parameter that had a positive correlation with the count of bacteria in the water, although this correlation was week (r = 0.18).

B. ANFIS Model Results

Table 1 shows samples of the fuzzy rules that define the mapping of the water quality parameters to the safety condition of the water. The network was trained using two different objective functions; triangular and Gaussian, each of which was composed of three membership functions (low, medium, and high). Thus, we applied 81 rules (3^4) in training the model using first order Sugeno type training algorithm. Results of the model from the two objective functions are presented in the subsequent sections.

Table 1. Fuzzy rules generated in the first ANFIS model with triangular MFs

Rule number	Rule
1	If (Bacteria is low) and (pH is low) and (Turbidity is low) and (Color is low) then Water Safety = 51.0337*B-1.1555*pH-7.7349*T-28.6089*C+3.2130.
…	…
74	If (Bacteria is high) and (pH is high) and (Turbidity is low) and (Color is medium) then Water Safety = -0.0254*B-0.0121*pH+0.0026*T+0.0002*C-0.0280.

1) Triangle Objective Function with 3 MFs

Fig. 3 illustrates the structure of the first ANFIS model used in classifying the safety condition of the water in the pipes. The rules indicated in table 1 were used to adjust these functions. The model has 81 rules but effectively there are only 40 rules with nonzero linear coefficients, effective rules are 1, 2, 4, 5, 7, 8, 10, 11, 12, 13, 14, 16, 17, 19, 20, 28, 29, 31, 32, 34, 35, 37, 38, 39, 40, 41, 43, 44, 46, 47, 55, 56, 58, 59, 64, 65, 67, 68, 73, and 74. The ANFIS model applies the adaptive capability to adjust the triangular membership functions until the classification error is minimized. This involves iterative mapping of the input parameters in the training data set with the aim achieving the least error.

The output of the classification of the first model is shown in Fig. 4. The training involved 125 data samples (70 %), while the testing data set constituted 55 samples. The target condition of the water were given threshold values; +1 for safe water and -1 for unsafe water. The same number of safe and unsafe samples were initially prepared, but the partitioning for training and testing samples was done by selecting random samples to constitute the 70% and 30%. This was meant to enable the model to adapt to a typical situation that may occur in the distribution pipes.

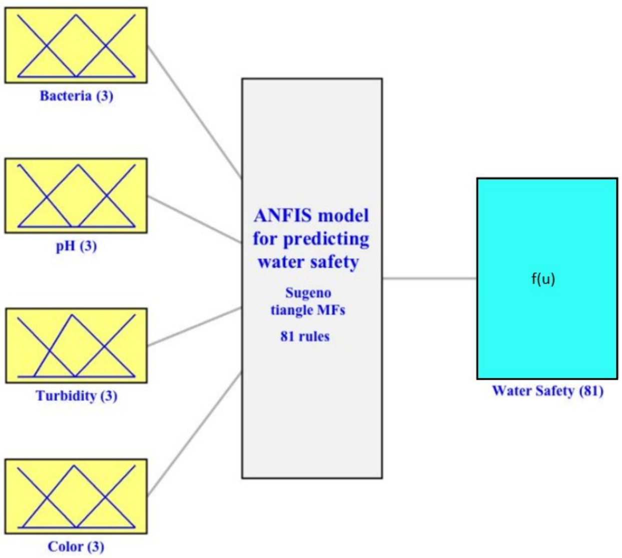

Fig. 3. Structure of the first ANFIS model trained using the triangular membership function

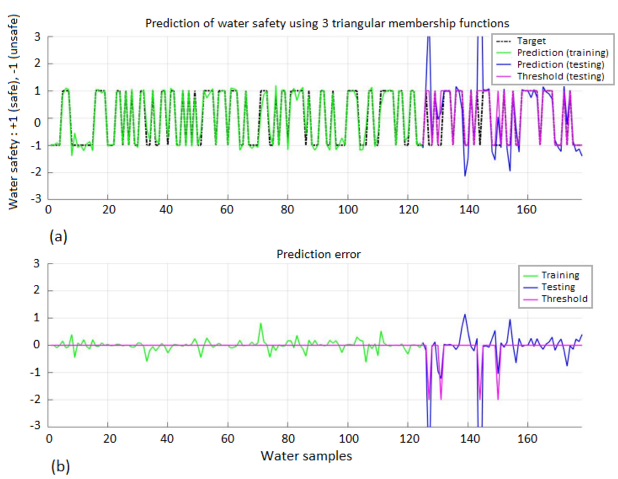

Fig. 4. Results of the classification of the safety condition of water samples during training and testing using the triangular membership functions.

It is evident from this plot that the model was capable of learning from the data set with very good accuracy. In some instances, the model could not predict values within the threshold values of +1 and -1. This may be an indication of overfitting in the model. However, majority of the training samples were within the threshold. During the model testing stage (shown in blue in Fig. 4 a), the model generally performed well, although significant over-predictions occurred, since the model predicted values beyond the thresholds. It can further be noted that there was only one occasion for which the model misclassified the safety condition of the water. This is obviously not very good, since it would have triggered a false alarm if the model were applied to the online sensors that measure the water quality parameters in the distribution network. We further set a threshold to the predicted values during the model testing stage to limit the range of values the model outputs. Results of the model testing after this imposed restriction showed distinct improvement over the previous model. The errors associated with the training and the two testing stages are shown in Fig. 4 b. This shows that, if the model is integrated with the sensors at the various locations of the distribution network, the safety or otherwise of the flowing water can be reliably determined with acceptable accuracy.

To further evaluate the performance of the ANFIS model, we computed the confusion matrix from the results of the training and testing stages. The outputs for the first model with the triangular membership functions are shown in table 2. The table compares the actual safety conditions of the water as used in the model training and testing, with the predicted safety conditions. The model made a total of 125 predictions during training, and 53 during testing, comprising 178 safety conditions (safe water (+1) and unsafe water (-1)). Thus, out of the 125 input samples, the model training stage predicted 63 safe water samples and 62 unsafe samples. The training stage therefore achieved a high accuracy without any false alarms. In the testing stage however, while the model predicted the exact number of safe water conditions (22 samples), 4 false negatives were predicted.

Table 2. Confusion matrix calculated from the results of ANFIS model 1 (triangular MFs)

Training				
n=125	predicted			
		+1	-1	
	+1	TP=63	FN=0	63
	- 1	FP=0	TN=62	62
		63	62	125
Testing				
n=53	Predicted			
		+1	-1	
	+1	TP=22	FN=4	26
	- 1	FP=0	TN=27	27
		22	31	53

2) Gaussian Objective Function with 3 MFs

Using the same model structure and inputs, the model was trained with Gaussian objective function. A total of fuzzy 81 rules were generated in the training process with the three membership functions. The resulting model structure after the training stage is shown in Fig. 5. Sample fuzzy rules used in the classification with this model are shown in table 3.

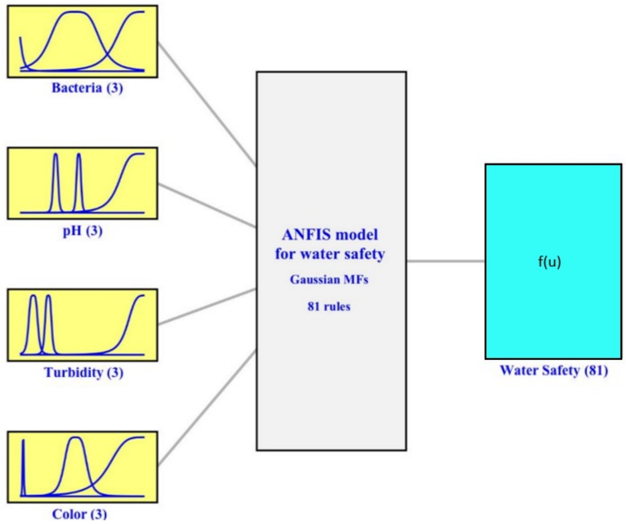

Fig. 5. Structure of the second ANFIS model trained using the Gaussian membership function

Table3. Fuzzy rules generated in the second ANFIS model with Gaussian MFs

Rule number	Rule
1	If (Bacteria is low) and (pH is low) and (Turbidity is low) and (Color is low) then Water Safety = 10.3898*B-5.2938*pH-2.1253*T-10.4479*C +0.1953.
…	…
81	If (Bacteria is high) and (pH is high) and (Turbidity is high) and (Color is high) then Water Safety = -0.5956*B+0.0389*pH-0.1652*T+0.0103*C-0.6996.

Fig. 6 shows the results of the second model. The training results of this model achieved very high accuracy compared with the previous model, with no discernible difference between the model predictions and the actual safety conditions. In addition, all the predicted classifications were within the threshold values of +1 and -1 used as for training the model. The level of accuracy is also reflected in the error associated with the training (Fig. 6 b). However, then the model was tested with the remaining data set, the accuracy level was similar to the previous model. The model could not reproduce the threshold values of +1 (safe) and -1 (unsafe), although fewer false misclassifications were achieved. The confusion matrix calculated from the results of this model is shown in table 4. This model predicted all the safe and unsafe water samples in the training set, just as the previous model. In addition, the model classified only two safe water samples as unsafe, compared to 4 misclassifications in the previous model. The imposition of restrictions on the threshold outputs of during the testing stage also resulted in significant improvement in the model. This suggest that with this restriction, both model structures can be applied in real time detection of the unsafe variations in the quality of water in the distribution pipes. It must be noted though that these models were trained with tighter regulations than the actual regulations in practice.

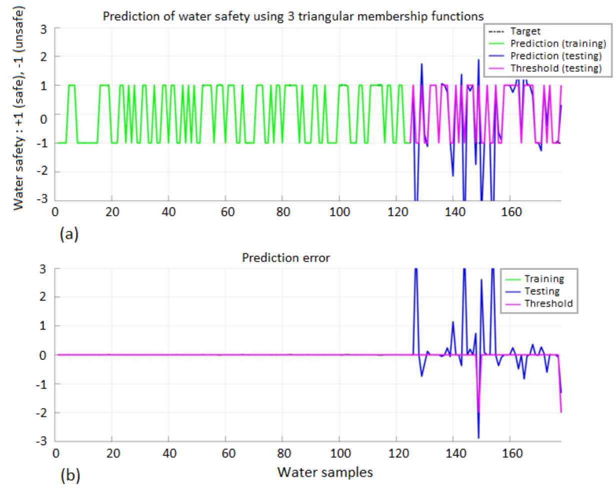

Fig. 6. Results of the classification of the safety condition of water samples during training and testing (a) and using the Gaussian membership functions.

Table 4. Confusion matrix calculated from the results of ANFIS model 2 (Gaussian MFs)

Training				
n=125	predicted			
		+1	-1	
	+1	TP=63	FN=0	63
	- 1	FP=0	TN=62	62
		63	62	125
Testing				
n=53	Predicted			
		+1	-1	
	+1	TP=24	FN=2	26
	- 1	FP=0	TN=27	27
		24	29	53

Moreover, we evaluated the effects of the various input parameters on the safety conditions of the water using the fuzzy relations generated in the models. Fig. 7 shows the surface plots of the fuzzy relations from the ANFIS model 1 with triangular MFs. Considering the effect of each input parameter, changes in the turbidity, color, and the bacteria count in the clean water have greater influence on the safety condition. However, the magnitude of the effect of each parameter depends on the variation of other parameters in the model. For instance, the effect of the interaction between turbidity and bacteria count (Fig. 7 b) indicate that lower turbidity values can be associated with unsafe water in the pipes, yet the effect of interaction with pH variation suggest that the water in the pipes can be more safe at lower turbidity values (Fig. 7 d). Similarly, Fig. 7 b suggests that higher bacteria counts can be associated with unsafe condition of the clean water, since lower values occur in the water safety column. However, at low pH and high bacteria count (Fig. 7 a), the opposite occurs. Based on the fuzzy relations, it is difficult to precisely determine the effect of each parameter on the safety/quality of the water without taking into account the effect of interactions with other water quality parameters [17]. Nonetheless, these fuzzy relations provide a means of understanding the overall effects of the water quality parameters on the safety, unlike other "blackbox" models that do not have such capabilities.

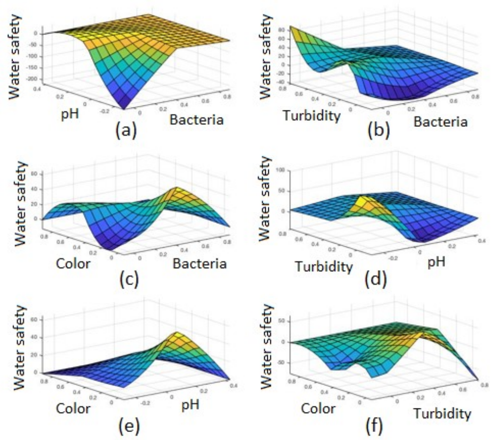

Fig. 7. Fuzzy relations between water quality variables and the safety condition of water in the distribution pipes.

The model performance indices evaluated during the training and testing stages are shown in table 5. The ANFIS model with the Gaussian membership functions achieved higher accuracy for the training and testing data sets, with mean absolute error values of 0.0025 and 0.4949 respectively. The predictions of this model was also highly correlated with the actual values present in the data.

Table 5. Performance indices of the two ANFIS models

Train			
ANFIS model	mse	mae	Correlation
Gaussian (3 MFs)	2.604e-05	0.0025	1.0
Triangular (3MFs)	0.0332	0.1092	0.9833
Test			
Gaussian (3 MFs)	1.275	0.494	0.751
Triangular (3MFs)	2.413	0.527	0.418

Finally, we used the information from the confusion matrices (tables 2 and 4) to calculate the error rates for the testing stages of both models. The overall testing accuracy of the ANFIS model 2 (with Gaussian MFs) was 96 %, compared to 92 % in the ANFIS 1 model (with triangular MFs). The error rates were calculated as follows.

ANFIS model 1 (triangular MFs):

- **Accuracy:** Overall, how often is the classifier correct?
  - (TP+TN)/total = (22+27)/53 = 0.9245
- **Misclassification Rate:** Overall, how often is it wrong?
  - (FP+FN)/total = (0+4)/53 = 0.0755
  - equivalent to 1 minus Accuracy
  - also known as "Error Rate"
- **True Positive Rate:** When it is actually safe, how often does the model predict safe?
  - TP/actual safe = 22/26 = 0.8462
  - also known as "Sensitivity" or "Recall"
- **False Positive Rate:** When it is actually unsafe, how often does it predict safe?
  - FP/actual unsafe = 0/27 = 0
- **Specificity:** When it is actually unsafe, how often does it predict unsafe?
  - TN/actual unsafe = 27/27 = 1
  - equivalent to 1 minus False Positive Rate
- **Precision:** When it predicts safe, how often is it correct?
  - TP/predicted yes = 22/22 = 1
- **Prevalence:** How often does the safe condition actually occur in our sample?
  - actual safe/total = 26/53 = 0.4905

ANFIS model 2 (Gaussian MFs):

- **Accuracy:** Overall, how often is the classifier correct?
  - (TP+TN)/total = (24+27)/53 = 0.9623
- **Misclassification Rate:** Overall, how often is it wrong?
  - (FP+FN)/total = (0+2)/53 = 0.0377
  - equivalent to 1 minus Accuracy
  - also known as "Error Rate"
- **True Positive Rate:** When it is actually safe, how often does it predict safe?
  - TP/actual yes = 24/26 = 0.9231
  - also known as "Sensitivity" or "Recall"
- **False Positive Rate:** When it is actually unsafe, how often does it predict safe?
  - FP/actual unsafe = 0/27 = 0
- **Specificity:** When it is actually unsafe, how often does it predict unsafe?
  - TN/actual unsafe = 27/27 = 1
  - equivalent to 1 minus False Positive Rate
- **Precision:** When it predicts safe, how often is it correct?
  - TP/predicted safe = 24/24 = 1
- **Prevalence:** How often does the unsafe condition actually occur in our sample?
  - actual safe/total = 26/53 = 0.4901

IV. CONCLUSIONS

This paper presented the development of classification models for predicting the safety condition of water in distribution pipes. The models, based on ANFIS technique, were built using water quality variables measured from the effluent of the water treatment plant in Ålesund, Norway, as well as seven different locations across the pipe network. Based on information from the Norwegian Guide to Drinking Water Regulations, the approved concentrations of the water quality parameters in treated water were used to initially classify the data into two conditions; "safe" and "unsafe". The resulting data was used to train and test the ANFIS models.

The proposed ANFIS models can correctly detect between 92% and 96% of the safety condition of the water in the pipe network, with approximately 1% false alarm rate during the testing stage. The models also achieved high rates of specificity and precision, with very high correlations between the predictions and actual conditions of the water in the pipes. Further, the ANFIS models explained the effects of the interactions of the various water quality parameters on the safety condition of the water in the pipes, with the effect of turbidity and bacteria counts being more distinct than the other parameters. Despite reducing the acceptable maximum threshold concentration of bacteria count in the clean water from 100 to 80 in this study, the accuracy of the models achieved in this study suggests that the models can be useful in real time detection of the safety condition of water in the pipe networks. This can be achieved by integrating these models with the online sensors at various locations of the pipe network where water quality parameters are regularly measured such that the safety condition of water in the distribution network can be assessed from each set of measurements from the sensors and an alarm can be triggered when necessary.

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REFERENCES

[1] Besner M. C., Prevost M., & Regli S. (2011). Assessing the public health risk of microbial intrusion events in distribution systems: Conceptual model, available data, and challenges. *Water research*, *45*(3), 961-979.

[2] Ercumen A., Gruber J. S., & Colford Jr J. M. (2014). Water distribution system deficiencies and gastrointestinal illness: a systematic review and meta-analysis. *Environmental Health Perspectives*, *122*(7), 651.

[3] Lambertini E., Borchardt M. A., Kieke Jr B. A., Spencer S. K., & Loge F. J. (2012). Risk of viral acute gastrointestinal illness from nondisinfected drinking water distribution systems. *Environmental science & technology*, *46*(17), 9299-9307.

[4] WHO (2015). Improving environment and health in Europe: how far have we gotten? Copenhagen: WHO Regional Office for Europe; 2015. http://www.euro.who.int/__data/assets/pdf_file/0018/276102/Improving-environment-health-europe-en.pdf (Assessed 22/03/2017)

[5] NIPH (2017). Norwegian Institute of Public Health (Public Health Report). Drinking water in Norway. https://www.fhi.no/en/op/hin/risk--protective-factors/drinking-water-in-Norway/#main-points (Retrieved 22/03/2018)

[6] Hart W. E., & Murray R. (2010). Review of sensor placement strategies for contamination warning systems in drinking water distribution systems. *Journal of Water Resources Planning and Management*, *136*(6), 611-619.

[7] Hasan J., States S., & Deininger R. (2004). Safeguarding the security of public water supplies using early warning systems: a brief review. *Journal of Contemporary Water Research & Education*, *129*(1), 27-33.

[8] Liu S., Smith K., & Che H. (2015). A multivariate based event detection method and performance comparison with two baseline methods. *Water research*, *80*, 109-118.

[9] McKenna S. A., Wilson M., & Klise K. A. (2008). Detecting changes in water quality data. *American Water Works Association. Journal*, *100*(1), 74.

[10] Klise K. A., & McKenna S. A. (2006, May). Water quality change detection: multivariate algorithms. In *Optics and Photonics in Global Homeland Security II* (Vol. 6203, p. 62030J). International Society for Optics and Photonics.

[11] Raciti M., Cucurull J., & Nadjm-Tehrani S. (2012). Anomaly detection in water management systems. In *Critical infrastructure protection* (pp. 98-119). Springer, Berlin, Heidelberg.

[12] Perelman L., Arad J., Housh M., & Ostfeld A. (2012). Event detection in water distribution systems from multivariate water quality time series. *Environmental science & technology*, *46*(15), 8212-8219.

[13] Jang J. S. R. (1993) ANFIS: adaptive network-based fuzzy inference systems. IEEE Transactions on Systems, Man, and Cybernetics 23: 665–685.

[14] Jang J. S. R.; Sun C. T. (1997). Neuro-Fuzzy and Soft Computing: A Computing Approach to Learning and Machine Intelligence. Prentice Hall, Englewood Cliffs, NJ.

[15] Sahu M., Mahapatra S. S., Sahu H. B., & Patel R. K. (2011). Prediction of water quality index using neuro fuzzy inference system. *Water Quality, Exposure and Health*, *3*(3-4), 175-191.

[16] Mohammed H, Hameed I. A., Seidu R. (2018). Comparative predictive modelling of the occurrence of faecal indicator bacteria in a drinking water source in Norway. Science of the Total Environment, 628, 1178-1190.

[17] Mohammed H., Hameed I. A., Seidu R. (2017). Comparison of Adaptive Neuro-Fuzzy Inference System (ANFIS) and Gaussian Process for Machine Learning (GPML) Algorithms for the Prediction of Norovirus Concentration in Drinking Water Supply. In *Transactions on Large-Scale Data-and Knowledge-Centered Systems XXXV* (pp. 74-95). Springer, Berlin, Heidelberg.

[18] Norwegian Guide to Drinking Water Regulations (*In Norwegian*). Mattilsynet statens tilsyn for planter, fisk, dyr og næringsmidler. https://www.mattilsynet.no/om_mattilsynet/gjeldende_regelverk/veiledere/veiledning_til_drikkevannsforskriften.25091. Retrieved 21.03.2018