Monitoring Water Consumption Using Machine Learning

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Abstract

This paper concerns one of the most important elements in economic life, which is water. Normally, the user, who is responsible to manage water services, is not aware about the consumption situation prior to issuing the bill, so, this research proposes innovative managerial techniques to monitor water consumption across the network. Machine learning is used through clustering techniques to achieve the monitoring goal, which contributes towards decision making, fault prediction, and data management processes.in facility management. Artificial Neural Network is the specific part of the chosen technique and Python is used as a tool to implement the method. A case study is applied in one of the universities and a network including six locations is studied at a specific time. The method shows a significant result where the consumption at three locations were found high and accordingly, the user made further inspection and continuous monitoring about the network in discussion.

Keywords
Machine Learning, Artificial Neural Network, Water Consumption, Monitoring and Clustering.

1. Introduction

As two third of the earth surface covered by water and the humans are using approximately 70 % of it (Baroni *et al*, 2007), it is significantly obvious that water is one of the prime elements responsible for life. At industry or business life, water consumption makes concern to those who are managing the said facilities and therefore, policies and plans must be placed to monitor its consumption and save the monthly bills accordingly.

There are number of studies were addressed monitoring water consumption, one of them was determined the volume of water consumed for the following events: 1) use of faucets, 2) toilet flush, and 3) shower in a particular building by interfacing sensor to a microcontroller to monitor fluid dynamics in real-time (Somontina *et al*, 2018). Another study was well implemented to monitor the water consumption in different purposes of the slate manufacturing plant using theoretical, experimental calculation/ analysis, and reporting-static methods (Sadikovna & Farhadovna, 2020). On the other hand, Internet of things (IoT) application is illustrated through a real implementation of global household water consumption monitoring system across two countries in Europe where a novel wireless water consumption monitoring system is designed, in which flow rate/temperature sensors are placed at different detection spots in a house to collect data, and the collected data is routed to a remote computer server via the home WiFi and the Internet (Yang *et al*, 2015). IoT was also used to monitor the domestic water consumption and behavior intervention in many households in China (Yang *et al*, 2017). In agricultural applications, a study was conducted by using scintillation techniques for monitoring seasonal water consumption of olive orchards in a semi-arid region (Ezzahar *et al*, 2007). Another study was integrated satellite-based evapotranspiration monitoring approach with two spatial resolutions over an extremely arid area (Tan *et al*, 2018). Having gone through these studies as well as others in other fields, it shows how monitoring water consumption is really a concerned task.

In this research, Machine Learning (ML) is applied for the same purpose of presented research but with a new innovative way. Clustering is used here, which is considered as the most commonly used unsupervised machine learning technique. It can be defined as the process of organizing objects into groups whose members are similar in some way and it is an optimization problem as well (Guttag, 2017). Specifically, in this paper, artificial neural network (ANN), which is one of the main types of clustering, is used. It is an interconnected group of nodes, inspired by a simplification of neurons in a brain (Chen *et al*, 2019). Figure 1 shows these nodes where each of them represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another. It has several applications in many water studies, one of them was applied it in water treatment process control where a neural network process model was well built for the coagulation, flocculation, and sedimentation processes (Zhang & Stanley, 1999). It was also used in water quality management where a neural network backpropagation algorithm was created to form a model to solve the multi-objective problems in Tou-Chen River Basin in Taiwan (Wen & Lee, 1998). Another study applied this application to forecast the water inflow in another river basin (Golob *et al*, 1998). In Netherlands, Aquarius Decision Support System was chosen as a reference model for building a controller for water systems using machine learning techniques such as ANN and reinforcement learning (RL), where RL was used to decrease the error of the ANN-based component and accordingly a good result was obtained (Bhattacharya *et al*, 2003). ANN was also used to estimate the average annual water supply in each mountainous watershed of Cyprus (Iliadis & Maris, 2007). Again, IoT along with ANN were both used for saving the wasted water in the process of irrigation based on a set of sensors as well as Multi-Layer Perceptron (MLP) neural network (Karar *et al*, 2020). ANN was also applied in water system management with regards to solar energy aspects where a study presented an optimal performance of three phase induction motor drives a centrifugal water pump and fed from photovoltaic (PV) system without storage elements during starting and running (Elkholy & Fathy, 2016). ANN can be combined with other techniques as well where a study was constituted it with regression analysis and chaotic nonlinear dynamic models in forecasting stream water temperature (Sahoo *et al*, 2009). Going back to clustering definition, ANN, however, is an optimization technique and is used in this research with a similar purpose. Having said that, ANN was used in optimizing water usage of smart farm automated irrigation system (Del Cruz *et al*, 2017).

In this paper, an innovative method is presented to help the user to better understand the water network at his/ her facility and identify the high consumption area using Python. The next section, which is the methodology, contains two parts, the first one prepares the user to arrange the required documentation and makes him/ her ready to move forward to the second part, which is applying neural networks on water facilities at any organization.

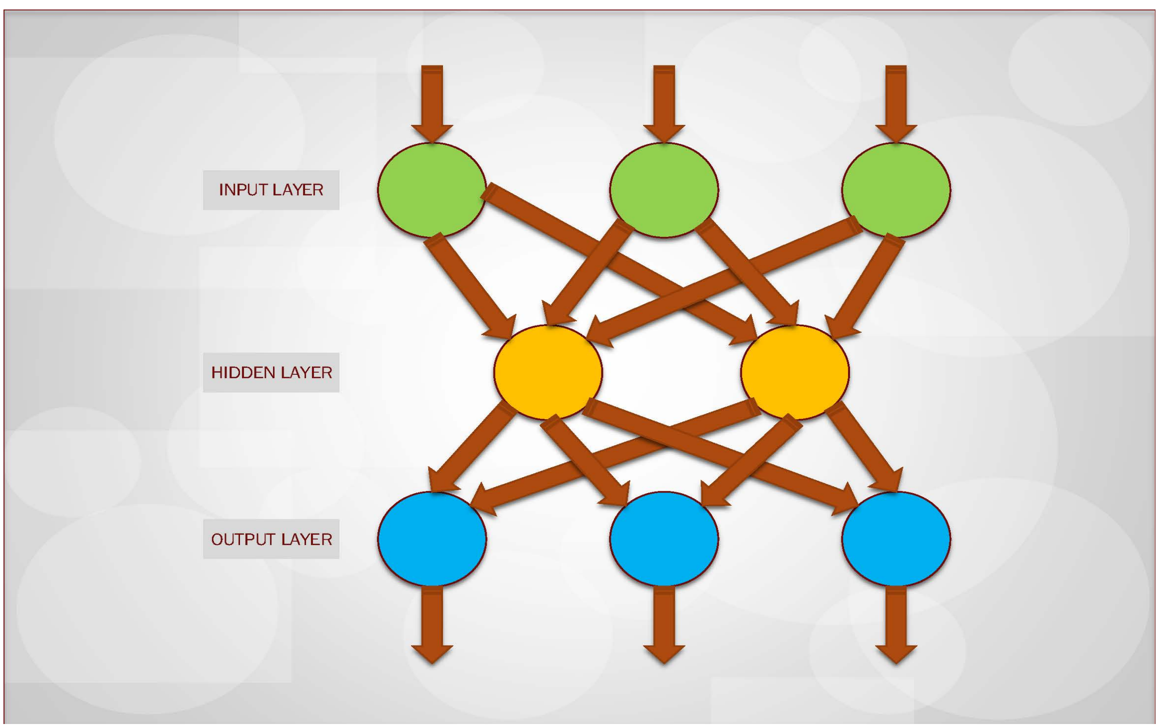


Figure 1. General Form of ANN Structural

3. Methodology

ML facilitates creating water usage trends and patterns for different data streams and Key Performance Indicators (KPIs), which consequently results in the optimization of resource utilization.

3.1 Water Network

As stated in the introduction, this part is proposing and recommending steps for the user to have a clear view about water network. These steps are sequenced as follow:

- Getting idea about previous water bills.
- Checking the history of water consumption of the whole organization.
- Addressing either the network of the whole organization or of a specific area.
- Requesting the As-Built drawing of area/ building that will be studied.
- Transferring and simplifying the previous drawing to a created template (Almobarek *et al*, 2020).
- Collecting the data based on convenient theme for each understudy location. It is advisable to be more than or equal 30 readings for each location.
- Making the same data ready to be read in Python by tabulating each location's data with the proposed format in Table 1. Excel is recommended to be used for this format. The user is recommended to make a sperate file for each location and consider the file name in Python later.

Table 1: Data Tabulated Format

Location.m
X_1
X_2
. . .
X_n

Where:

m: Location number.
X's: Water consumption in cubic meter at a specific period.
n: Sample size.

3.2 Self-organized map (SOM) Structure and Training

A two-dimensional SOM network is used to cluster the water consumption into high or normal consumption. The network is expected to identify the anomalies in water consumption where water consumption is above a normal level. The network consists of an input layer with 1 node representing the water consumption and a two-dimensional lattice of nodes in the output layer representing the clustering scheme. The input and the output layers are fully connected. The input data is read from the dataset as specified in section 3.1. Different lattice structures were investigated for the output layer ranging from a 2X2 to 6X6. A 4X4 output layer was found to perform well in identifying irregular consumption. The network topology is shown in Figure 2.

The network training starts with initiating the weight matrix with random values. An input vector is chosen at random from the water consumption dataset and presented to the network. Using the Euclidian distance, the weight vector connected to each node in the output layer is compared to the input vector to find which weight vector matches the input vector. The node that corresponds to the minimum Euclidian distance is considered the winning node and labeled as the Best Matching Unit (BMU). A neighborhood of the BMU is identified with a preset radius. Different neighborhood radiuses were examined and a radius of 3 was found to be the best in identifying distinguished clusters. The weight of the BMU and its neighbors' nodes are adjusted so their weight becomes closer to the input vector. The updated weight is calculated using the equation (Eq.1). The learning rate (α) was set to 0.3 after investigating different values. The neighborhood decays as the training progresses until it is only left with the BMU. The training process is repeated to include all the training dataset where 150 iterations are performed at each point. The clusters are visualized with a color-coding map. In the greyscale map, the lighter the node the higher values of water consumptions it represents.

$$\text{Adjusted Weights} = \text{Current Weights} + \alpha\,(\text{Input Vector} - \text{Current Weights}) \quad (1)$$

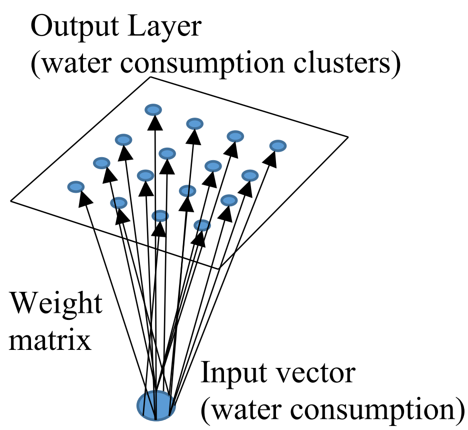


Figure 2: SOM Lattice structure

4. Application & Results

College of Business building at Alfaisal University is chosen to be a case study for this research. Three water systems are serving it, which are potable, non-potable, and irrigation. Each system is connected to two zones, which are inner-ring and outer-ring, so the total number of locations need to be studied is six. Water consumption data for each location is collected over one week at one-hour intervals. An Excel file for each location is created with the names L1, L2, L3, L4, L5, and L6. Then, neural network lattice is applied, and the six files have been read in Python. After running the codes, the resulting self-organizing map shows that locations 1, 2, and 4(represented by the circle, rectangle, and triangle respectively), which are potable system for both inner-ring and outer-ring as well as non-potable system for outer-ring, have high water consumption. Accordingly, the user has inspected the site and found real technical issues like small leakage, faulty wash basin's battery, and malfunctioning of water closet push button, respectively. Figures 3 & 4 show snapshots of Python outcomes. A plan is made through building management system (BMS) to check all six locations regularly and automatically. This plan is like integrating the water consumption data within BMS intelligently (Clark & Mehta, 1997).

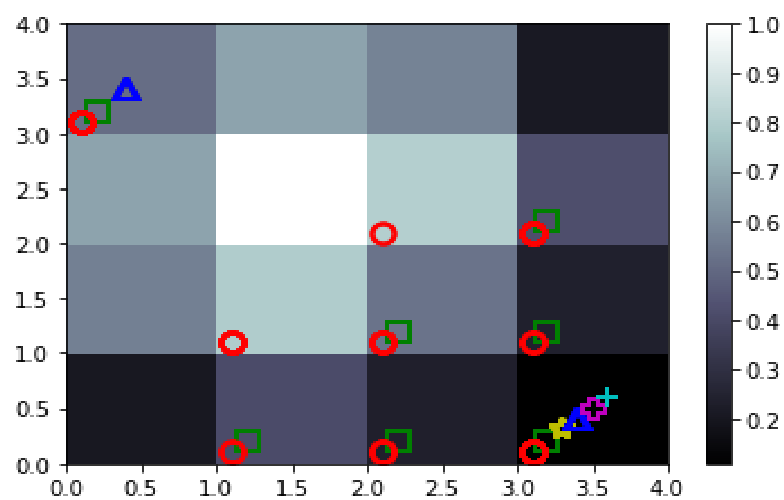
In [6]:
```
pip install minisom
```

```
Requirement already satisfied: minisom in c:\users\hp\anaconda3\lib\site-packages (2.2.6)
Note: you may need to restart the kernel to use updated packages.
```

In [67]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset = pd.read_csv('L1-L6.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
from minisom import MiniSom
som = MiniSom(x = 4, y = 4, input_len = 1, sigma = 3, learning_rate = 0.3)
som.random_weights_init(X)
som.train_random(data = X, num_iteration = 150)
from pylab import bone, pcolor, colorbar, plot, show
bone()
pcolor(som.distance_map().T)
colorbar()
markers = ['o', 's','*','^','P','+']
colors = ['r', 'g','y','b','m','c']
for i, x in enumerate(X):
    w = som.winner(x)
    if y[i]== 0 :
        plot(w[0] + 0.1,
             w[1] + 0.1,
             markers[y[i]],
             markeredgecolor = colors[y[i]],
             markerfacecolor = 'None',
             markersize = 10,
             markeredgewidth = 2)
    elif   y[i]== 1:
            plot(w[0] + 0.2,
```

Figure 3: Snapshot of Files' Reading in Python

```
show()
mappings = som.win_map(X)
```



In [ ]:

In [ ]:

Figure 4: Self-organized output map

5. Conclusion

In this paper, we have proposed a water consumption monitoring method using Self Organized Maps (SOM). The SOM was trained using real water consumption data collected from Alfaisal University water network. This study shows the visualization abilities of Self-Organized Maps to detect water over usage with easy visualization and interpretation. The proposed methodology can be integrated with the building management system and provide information to the facility managers about the abnormal water consumptions at different locations for further investigations. The results obtained have proved the effectiveness of SOMs for monitoring water consumption which can be implemented readily in smart buildings.

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Biographies

Malek Almobarek is a Saudi national. He was born on April 1983 in Kuwait City. He took his primary and secondary education at AlMawardi School where he was a consistent honor student. He graduated in Industrial Engineering from King Saud University in the year 2009. He did assistance to his professors at the same university with tutorial & site visits for the students before starting his experience journey by taking up a job as Plants Equipment Specialist in O&M department at GASCO, Riyadh. He worked there from May 2009 to Sep 2011. He then moved to Dallah Hospital, Dallah Health Co., Riyadh to work as Engineering Department Manager from Sep 2011 to Nov 2013. Thereafter, He joined Alfaisal University as Facility manager in Dec 2013 and currently discharging his duties as Senior Facility Manager. The areas of responsibility in his current job include Buildings and grounds maintenance; Projects; Cleaning; Catering and Leasing; Health and Safety; Procurement and Contract management; Security; Space management; Waste disposal; Mails, Housing and Transportation; Utilities and Campus infrastructure. It is here that he decided to further his studies while continuing to work and joined in Master of Engineering Management (MEM) program that Alfaisal University was offering. He scored GPA 4.0/4.0 and completed a research thesis on Water Budget Control Framework Using DMAIC Approach for Commercial Buildings. He graduated in April 2020 with a first honor and now is a full time PhD student in Design, Manufacturing and Engineering Management at University of Strathclyde, UK. Eng. Malek is a result oriented, Innovative, resilient, and collaborative. He is not only very good in academics, but also, he is an expert in Facility and Project Management; Procurement and Inventory Management; Supply Chain Management; Emergency Response; Environmental Control; Security Control; Contractor Oversight; Resource Allocation; Building Regulations; Building Systems; Fire Safety; Scheduling; Processes and Procedures; Hazardous Waste, etc. He is a member of Saudi Council of Engineering in the capacity of Professional Engineer and loves travelling, reading, bowling, and watching debates on TV.

Abdallah Alrshdan is an assistant professor in Industrial Engineering at Alfaisal University, Saudi Arabia. He teaches courses in Ergonomics, Work Design, Data analytics, and Quality Engineering. His PhD in Industrial Engineering is from Wichita State University. His current research focuses on ergonomics product design, applications of AI in the design and manufacturing process, and lean production. He worked as a production manager at ALL Cell technologies in USA building Li-ion batteries used for electrical cars and continues as a consultant in the research and development department. Dr. Alrshdan is currently the chair of the Industrial Engineering department and the head of quality assurance. He serves as a reviewer for different international journals and session chair in international Industrial Engineering conferences.