Study the Effect of Precipitation on the Performance of Wastewater Treatment Plant using KSOM

Syed Abbas Hussain Rizvi
School of Energy, Geoscience, Infrastructure and Society
Heriot Watt University, Dubai Campus
Dubai, UAE

Rabee Rustum
School of Energy, Geoscience, Infrastructure and Society
Heriot Watt University, Dubai Campus
Dubai, UAE

***Abstract*— The main area of concern in water and wastewater engineering is the treatment system that involves the transportation, disposal and purification of water. There is a need for extra care in water treatment as it leads to disease outbreak if it is not being handled properly. Therefore, with so many factors involved in treatment system, it becomes a very complicated process for the engineers where they have to monitor all the aspect of the treatment system in order to avoid any faults. One of these factors is precipitation which contributes a significant input to the wastewater treatment system. Hence, to analyze the effects of precipitation, self-organizing map (SOM), an unsupervised artificial neural network, is used to study the effects of precipitation on the performance of wastewater treatment plant. This paper used data collected from a wastewater treatment plant in San Diego, California for a period of 5 years. The results of the case study showcased a tool which was able to recognize the relationship among different parameters with rain in the wastewater treatment system. The 2D component plane of the SOM showed a positive correlation of rain with nitrates, pH and flow while a negative correlation with the Biochemical chemical demand (BOD), Chemical oxygen demand (COD), Suspended Solids (SS), ammonia and phosphate. Finally, this study shows the merits and disadvantages of monitoring the treatment system with SOM tool.**

Keywords; Self organizing map, Wastewater treatment system, Precipitation.

I. Introduction

Wastewater treatment plants are used to reclaim water and save the receiving water course from physical, chemical and biological pollution. Therefore, it is important for these systems to not only maintain control over the operation stages but also to improve it for more efficient purification of wastewater [1]. But, due to the complexity and uncertainty of the treatment system, mathematical models have been introduced to improve by understanding the relation between the process parameters. Most of the models have been developed using operational data without studying the effect of precipitation on the performance WWTP [2],[3].

Precipitation transforms to runoff when it falls on paved surface that enters the drainage system and hence overload the wastewater treatment system and affects its performance due to the tremendous increase in hydraulics and organic loads. As a result, it has become a significant concern for water engineers to control the treatment system [4], [5]. Hence, to analyze the effects of precipitation on different parameters, Self-organizing map, an unsupervised artificial neural network, was used.

ANN has the ability to relate input data with output variables in a complex system without the need of understanding the physics involved in them. It is defined as computing system that is made by many single interconnected processed elements that process information by using their state response from the external input provided. They tend to learn by example just like an infant that is observing an adult. Most commonly it is divided into supervised and unsupervised learning [2].

Supervised learning is when the system is given both the output and input data. It uses the input as the starting data and compares with the output to determine any errors. On the other hand, in unsupervised learning, there is not output data given to the system and it has to discover it on its own. This type of learning normally deals to solve complex data that is difficult to interpret by humans [2], [6]. Self-organizing mapping is the key tool for this type of learning that will be described in next sub-section.

This paper used the SOM to study the effects of precipitation on the performance of wastewater treatment plant.

A. *Self-organizing map:*

1) *Basics of Self-organizing maps:*

As one of the most widely used artificial neural network, the Kohonen self-organizing map is presented as dimensional grid or map whose nodes or neuron are tuned by the different input data or patterns. It is an unsupervised learning algorithm, therefore its training is data driven where the nodes compete each other [2].

The main objective of the self-organizing map is to transform the incoming signal pattern of arbitrary dimension into a two dimensional discrete map. It involves clustering of the input patterns in a way so that similar patterns are represented by the same output neuron or by its neighbor. Hence, it is a tool that can reduce the amount of data by clustering which converts the complex and non-linear relationship among the high dimensional data into a simple relation on a low two dimensional display [2].

Figure 1 illustrate the training of KSOM where it consists of two layers that are the multidimensional input and the output

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layer which is interconnected. The output layer contains M neurons arranged in two dimensional grid nodes where each neuron or nodes i (i=1, 2, 3, 4….M) are represented using the reference vector or n-dimensional weight in which n represents the dimension of the input vector or the number of variables in the input vector. Moreover, to determine the number of neuron, the following equation is used:

$$\mathrm{M} = 5\sqrt{\mathrm{N}} \tag{1}$$

Where N represents the total number of data samples. When M is known using this equation, the number of columns and rows can be determined in the KSOM by using:

$$\frac{l_1}{l_2} = \sqrt{\frac{e_1}{e_2}} \tag{2}$$

Where l_1 represents the number of rows and l_2 represents the number of columns, e_1 represents the largest eigenvalue of data set and e_2 represents the second largest eigenvalue [2].

2) Training of SOM

Firstly, the input data are standardized by finding the mean and standard deviation. The mean is deducted and divided by the standard deviation. A Standardized input vector is chosen at random and presented to each of the neurons for comparison with their respective code vectors to identify code vector which is the most similar to the input vector. To find the distance from the input, the following equation is used:

$$DistfromInput^2 = \sum_{i=0}^{i=n} (I_i - W_i)^2 \tag{3}$$

Where I represent current input vector, W represents node's weight vector and n is the Number of weights. This equation is called the Euclidean formula. The vector of the neuron that closely matches the input vector data is chosen as the best matching unit or the winning node mentioned in figure I. The weight vectors of the winning node along with the adjacent neuron are then adjusted in order to match it with the input data using the equation below:

$$W_i(t+1) = W_i(t) + \theta(t) L_{ci}(t)(I(t) - W_i(t)) \tag{4}$$

Where W(t+1) in the equation represents the new, educated weight value of a given node, t represents time $\Theta(t)$ represent the learning rate at time t and Lci(t) is the neighborhood function centered in winner unit c for time t.

Hence, in this manner every node in maps, internally, can recognize the input vectors that are very similar to it. This ability itself is called self-organizing since no external information is supplied that can lead in a classification. The adjustment and comparison process continue to the point where the specified errors are attained. Also, the learning rate and the neighborhood function must be chosen with care as it affects the learning effectiveness of the SOM tool. Furthermore, the learning rate decreases with increased number of iteration as shown below:

$$L(t) = L_0 (0.005 / L_0)^{\frac{t}{T}} \tag{5}$$

Where L_0 is the initial learning rate and T is the training length which causes the weight vectors to converge. The neighborhood function is chosen to be Guassian centered in the winner unit c as shown in equation below:

$$h_{ci}(t) = \exp\left\{ -\|r_c - r_i\|^2 / \left[2\sigma^2(t)\right] \right\} \tag{6}$$

Where r_c and r_i is equal to the position of node in c and I for the SOM grid and $\sigma(t)$ is neighbor radius. Just like the equation, it decreases with the increased number of iterations.

Once the training is complete, its quality is measured by the total topographic error and the average quantization error. The topographic error is shown by the below equation:

$$t_e = \frac{1}{N} \sum_{i=1}^{N} u(X_i) \tag{7}$$

Where u_i is the binary input that is equal to one if the 1st and the 2nd best matching units are not adjacent units for X_i, else it is equal to zero. The quantization error is found using:

$$q_e = \frac{1}{N} \sum_{i=1}^{N} \|X_i - W_c\| \tag{8}$$

Where q_e stands for quantization error, X_i is the ith vector and W_c is the prototype vector of the BMU (Best matching unit) for X_i [2].

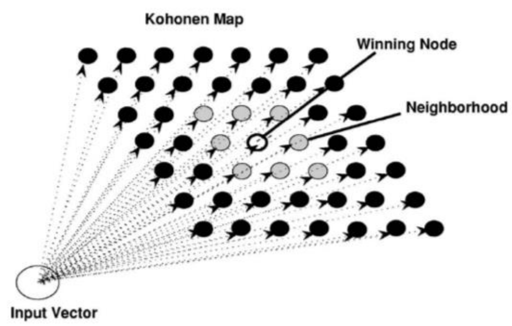

Figure 1 Training of SOM which shows the winning node and its neighborhood

The application of KSOM tool comes in various tasks. Some of these tasks have been described in the next section.

II. Literature review

The application of KSOM ranges from river flow, water quality, rainfall-runoff relation, modelling, interpolation, model identification and generalization [7].

The SOM has been used to regionalize areas in western England and Wales based on characteristics such as the catchment area, main stream length and slope, mean annual precipitation and soil index rather than geographic proximity. Ten neurons were used in the output layer of the SOM which after training would map sites with similar characteristics to the same neurons in output layers. SOM grouped the neurons into 3 classes which gave 3 homogenous regions for the sites. Furthermore, to show the amount of data SOM can handle, another research in Taiwan served the same purposes of regionalizing based on the 17 characteristic or variable including precipitation for 154 sites. Eight homogenous regions where obtained by simply dividing the output layer neuron to 8 clusters where SOM was able to regionalize these regions accurately. This grouping benefits areas that are geographically remote as it transfers information from gauged sites to ungauged sites [7].

As for the other applications of SOM, another study used rainfall and runoff relation of Kentucky River catchment and its physical properties to categorize the flow hydrograph into different segments. A flow hydrograph is a graph of flow against time and it shows the peak flow along with time. It has areas where flow varies with time which is affected by the catchment characteristics especially precipitation. As precipitation is converted to runoff, it becomes a significant input from drainage to wastewater treatment system. Arranging the hydrograph into different segments will allow to find the maximum time for the maximum input into the drainage system which will affect the chemical influents. Therefore, the outcome of the case study shows that SOM was able to find the number of segments just by the catchment data without any prior knowledge of the hydraulics involved. Moreover, it allowed for a compression of information by categorizing the hydrograph allowing for ease in transmission to understand it [7].

Some other case studies showcased SOM as a tool for forecasting rainfall estimates as well. SOM works as classifier for textural feature vector obtained from satellite data along with other models to provide an estimate. This is another benefit to forecast high intense rainfall to prepare the treatment systems for the necessary input [7].

SOM has been applied to solve many problems in wastewater treatment plants and been conducted that fulfill various purposes in various stages [2], [3], [8]. One such study by Ozer Cinar, determines the cause of high effluent concentration for fecal column, Biological oxygen demand (BOD) and total suspended solids (TSS) coming from phlegm wastewater treatment system. Using the operational data, the variables where clustered by the SOM and it allowed to evaluate the cause of high concentration of effluent just by looking at the final 2D shape presented by the SOM. These 2D outputs are compared for the effluent and the process input variables such as dissolved oxygen concentration, temperature etc. where an identical pattern between the input and output suggested for a correlation between them hence finding the responsible variable. The result found that low pH in biological reactor was the cause of these high effluents as the areas in 2D plane of pH was low (light color) for that of effluents which was high (dark color) [8]. This showed the possibility of using SOM in monitoring plant leading to further researchers on it [9]. One such research was done by Stephane Grieu and his team on WWTP in Saint Cyprian, France to measure the parameters that included chemical oxygen demand, suspended solids and ammonia. Using operational data of 4 years, the results obtained established a relationship among these parameters from the final 2D shape. This relationship was a positive correlation between dissolve oxygen and influent flow with chemical oxygen demand influent, ammonia influent and suspended solid influent [9]. The quick way through which SOM established these relations by just using a simple mapping led to another case where the idea was to use the tool as filter. The objective was to determine the parameters that directly affect the primary clarifier in the treatment system. With multiple variables being monitored it became hard to specifically pinpoint the responsible parameters that are affecting the primary clarifier. But with the ability of SOM to handle lot of operational data, the result showed a negative correlation of flow with suspended solids and biochemical oxygen demand as high flow rates are linked with low concentration of the 2-water quality [10]. The responsible parameters where pinpointed and this established a correlation between precipitation as flow with other parameters. This link between rainfall and flow is because of Rainfall-runoff relationship [5].

Rainfall acts as one of the inputs to treatment inflow water as it gets converted to runoff once it gets contacted with impermeable surface. The relationship between them can be complex with multitude factors contributing among them. The best way to understand them is with the use of soil capacity. As precipitation occurs, the water tends to fill up the soil which reduces it capacity to the point that it is full. The remaining water then acts as a surface runoff [5].

The precipitation’s impact on WWTP has been studied by some scholars previously [4], [11]. One of these scholars, Richard Mines’s research showed a moderate correlation of rainfall intensity with biochemical oxygen demand influent and total suspended solid influents when monitoring 24 WWTP in Georgia, USA. The result showed precipitation having negative correlation with BOD and SS concentration at period of high flow. It suggested that during excessive rainfall the concentration of influents in mg/l gets diluted therefore reducing their value that comes in the WWTP [11]. This result coincides with some of the case study that had precipitation as parameter in SOM [2], [10]. Furthermore, Erin Mcmahan took a more extensive tabular approach and found the effects of Rainfall on both the influent and effluent biochemical oxygen demand and total suspended solids. The result showed positive relation between them but in terms of load rather than concentration [4]. This meant that although the concentration of the BOD and SS influents decreases with excessive rain, the same time, there is an increased inflow coming into the treatment system that causes an increase in mass of these substances. However, with the complex process of wastewater treatment system all these researches doesn’t link precipitation with every single parameter, hence some of them are left out such as ammonia, phosphorus and chemical oxygen demand. These parameters such as phosphorus and ammonia have harmful effects that cause eutrophication and toxic buildup of tissue in aquatic life, therefore making it necessary to establish the link that cause them [12], [13].

III. Methodology

A. Data Collection:

For identifying the effect of precipitation on different parameters, a real-time data was taken from Loma treatment plant in Sand Diego, USA for a period of five years. The treatment plant itself is the largest WWTP in the metropolitan wastewater system. It works as a primary treatment system for the data taken where it can treat one hundred and fifty-five million gallons of sewage per day for 2.2 million people. The treatment plant involved series of stages starting from screening, grid chamber, primary clarifier, effluent bar screens, anaerobic digester, waste gas burner and cogeneration gas utilization facility. In addition, it uses anaerobic digestion to treat solids and convert them to methane as bio fuel for their generators making use of renewable energy. The plant is further linked with north and south bay water reclamation point along with the metro biosolid center that treats the sludge and most of effluents coming from it before discharging it to point loam outfall [14]. A schematic of the system is provided Figure 2.

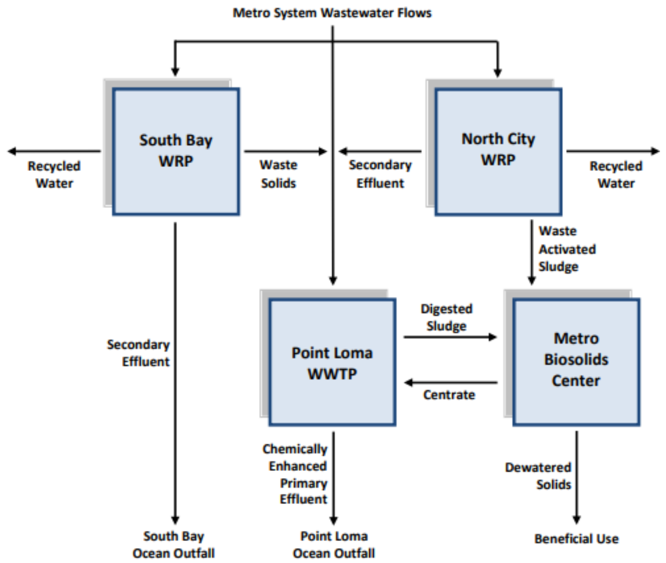

Figure 2 Overview of the treatment system [14]

The obtained data is comprised of sixteen variables which were taken from the time period of 2012 to 2016 mentioned in Table II.

Table I Monitored parameters

Parameters	Min.	Max.	Avg.
Precipitation (mm)	0	1.84	0.38
Influent (m^3/d)	479233	588253	528935
SS influent(mg/l)	311	394	355
BOD influent(mg/l)	286	362	323
COD influent(mg/l)	598	832	685
NH_4 influent(mg/l)	33.5	41.4	37.2
NO_3 influent(mg/l)	0	1.05	0.10
PO_4 influent(mg/l)	3	7.8	5.1
Temperature (Celsius)	22.7	28.7	25.8
pH	7.26	7.49	7.39
SS effluent (mg/l)	23	74	34.5
BOD effluent (mg/l)	99	160	116
COD effluent(mg/l)	201	365	259
NH_4 Effluent(mg/l)	33.3	40.4	37
NO_3 effluent(mg/l)	0	2.2	0.5
PO_4 effluent(mg/l)	2.4	6.7	4.61

Table II summarizes the input variables in the category of minimum, maximum and average values. The maximum influent received per day was 588253m^3 for the curse of five years where all the incoming flow is treated on the stage of process mentioned earlier. The COD influent is more than the BOD influent where it has a BOD to COD average ratio of less than 0.5 implying that there is more non-biodegradable substance in the waste. Also, when looking at the effluents, it is more than the limitation provided by US EPA for SS and BOD, but as it is the primary treatment system, the effluent goes for further treatment meaning that these effluents aren't the one to be dispatched on the watercourse. With the accurate data in hand, the next section details the procedure of the experiment.

B. Procedure:

MATLAB software was used in which self-organizing map is embedded that highlights the complicated relationship between these parameters (data) by presenting in a suitable summarized 2-D data for the purpose visual aid. EXCEL was used to arrange the initial data obtained from the WWTP. The step involved were of the training and searching of BMUs with the default values of learning rate being 0.5 and neighborhood radius as $[L_0 = \max(l_1, l_2)/4]$ where $l_1$and l_2 are dimension size of the map. While computing the size and dimension, the SOM tool uses Eq. 2 but adjust the final map units such that it is equal to the product of l_1 and l_2. While making these adjustments, the estimated map units might slightly be different to the ones obtained using Eq. 2. The resulting map units obtained where 40 which gave the sides of $l_1$and l_2 to be 8 and 5 respectively. The final quantization and topographic error was 2.502 and 0 respectively. The characteristic of SOM is summarized in the table below:

Table II Characteristic of the SOM

Normalization method	'Var"
Neighborhood function	Guassian
Map size	8 by 5
Lattice	Hexa
Final quantization error	2.502
Final topographic error	0.000

IV. Results and Discussion:

The beauty of SOM is the display of data presented in Figure 4. The results display each parameter in 2-D plane represented with colors that's helps to visualize an abundance of information quickly. Thus, when comparing each parameter mapping, the idea is to look at the identical colors. These colors represent a set of values which are lowest for the blue color and the highest for the red color as shown in Figure 5. For instance, when comparing the mapping of influent and effluent of NH_4, it shows a positive correlation as the areas which are blue color (lower value) for influent is in the same place of the effluent. This phenomenon is also true as when the influent is going to be at a higher quantity then the effluent is also going to be at a higher quantity which validates the results obtained from SOM to be correct.

The U-matrix of the system which is given in Figure 5is also displayed that works as a key where the color determines the distance between these neurons. It shows the distance of the vectors with the neighboring neuron.

Each of these 2D mapping parameters where linked with 2D plane of precipitation to analyze any correlation among them. Areas with higher rainfall (red color) in SOM were compared in the same area for each of parameters as the idea is to see how high rainfall affects them. Multiple parameters should correlation which is described in the next sub-section.

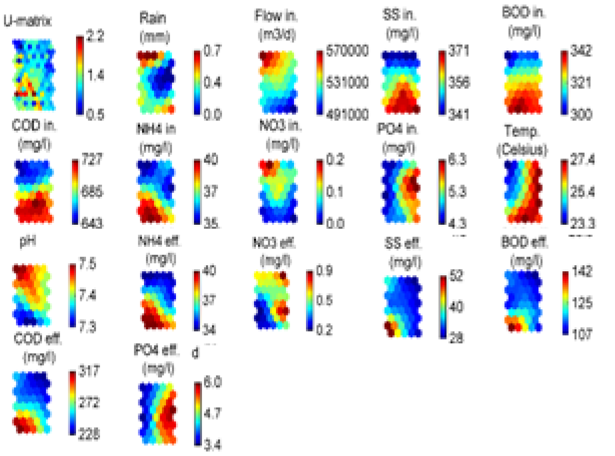

Figure 4 Component planes of SOM

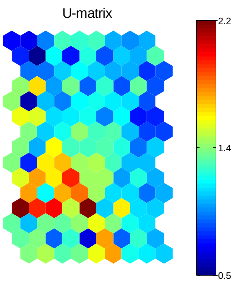

Figure 5 The U-matrix of the final output

A. Precipitation compared with Flow, pH and nitrates:

Beginning with the relation of flow and precipitation, the both planes are very identical to one another. This shows them having positive correlation where the higher (red color) is in the same position for both precipitation and flow. This is also supported with the relationship of Rainfall and runoff described earlier that contributes as an influent to the treatment[15]. Furthermore, the city of San Diego is an urbanized area [16] which favors more paved roads (impermeable surfaces) that doesn't allow precipitation to infiltrate in soil, thereby converting them to flow. Similarly, to flow, nitrates and pH component also gives a positive correlation with precipitation.

The positive correlation of pH and precipitation shows that the idea of more alkaline substance coming in treatment system. These alkaline include ammonia that is seen coming at larger quantity (33-41mg/l) in figure 4 than the acidic nitrate (0.1-0.2mg/l).

Moving towards nitrates, they are found in the form of sodium nitrate and in fertilizers. However, the city itself doesn't contains nitrate deposit neither it is a suburban area which utilizes nitrates in fertilizer. Therefore, it means that the source of nitrate in the city comes as the by product in thunderstorm that is surrounded with the presence of nitrogen-oxygen rich atmosphere. Moreover, the formation of such nitrate is very less which is also supported in the SOM with value ranging from 0.0mg/l to 0.2mg/l [17]. Therefore, when precipitation increases, higher number of nitrate influent are formed that is justified in comparison of the two 2D planes. The second sub section links the other parameter with precipitation and each other.

B. Relationship among Precipitation, COD, BOD, PO_4, SS and NH_4:

The relationship among COD influent, BOD influent, SS influent and NH_4 influent is a positive correlation with each other but a negative correlation with precipitation. According to theory, there is no direct relationship or links between Suspended solids and BOD, however, according to numerous case studies mentioned in the literature review section [8], [10], SS and BOD tend to be proportional to each other. The same pattern has been observed here with the plane of both parameters linking each other further strengthening the evidence found in previous case studies. On the other hand, the link between the plane of COD and BOD is proportional which is justifiable as COD measures all the chemicals that can be oxidized in water while BOD measures amount of food/organic carbon which the bacteria can oxidize. Both are correlated with a ratio 1: (0.6-0.8) for COD and BOD respectively further evidencing on their proportionality [18].

Moving towards the negative correlation, if the inflow is high due to precipitation then there should be higher suspended solids and BODs coming into the system. Their 2-D plane doesn't represent that due to the way the data was collected because when SS, BOD, COD and NH_4 influent concentration are having low value in mg/l, the incoming flow is high in m^3/d which means that the overall mass in mg/d will increase due to precipitation. Furthermore, these solids (inorganic) are found in limited quantity on the ground and with precipitation, these limited quantities get diluted when added to the wastewater treatment influents as inflow as also seen in [11]. Also, the same negative correlation is observed when comparing precipitation with PO_4. As phosphate produces phosphorus that contributes to eutrophication, higher precipitation tends to dilute its concentration.

The relationships between precipitation and effluent parameters establishes similar relation as the influent due to the fact that the main objective of the treatment was to remove a set number of quantities from the influent. This means that the effluent is nothing but mathematically reduced values of their influent, hence sharing an identical pattern with their influent therefore the same correlation with precipitation, this is only in case of primary treatment as there is no biological reactions to consume organic materials. Also, some of the substance such as PO_4 has not been reduced significantly as other because they are treated in the metro bio solid center, not on this primary treatment system [14].

To conclude, these relations set an important understanding of parameters with precipitation where it allows the treatment system to prepare for scenario of high rainfall where enhanced influents come into the system. For each influent, the set stages that remove them can be improved/enhanced to allow the treatment to perform efficiently.

V. Conclusion:

The sole purpose of SOM in this study was to establish multiple relationships among the parameters with precipitation using real time data provided by the San Diego WWTP. The ability of this tool to handle multiple parameters in a matter of short time allowed for quick snapshot of the result in a 2D plane. Moreover, it was ideal when presenting pre-process data which assists in deciding the important parameters that must be taken care of, when affected by precipitation. Also, the way it displayed the final output, it removed the problem of having to compare multiple line or bar graph that would have represented each parameter.

The results show the effect of increased precipitation caused an increase in flow, pH and nitrates while a decreased in the contents of Suspended solids, NH_4, BOD and COD in mg/l at a higher effluent rate. Furthermore, it would have showcased positive relation with BOD, SS and COD.

VI. Acknowledgement:

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VII. Reference:

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