Optimization of Water Wells Production for Water Cleaning Process

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Abstract: This paper presents a model to optimize water Well production for a water cleaning process to maintain the pollution level of a polluted ground water area with 20 Wells of varied pollution concentrations. In Hungary, a pharmaceutical company contaminated an area by using different chemicals to manufacture drugs. The production area has Wells with different concentrations and needs to be cleaned to maintain a constant pollution concentration. I cannot discuss the company, its location, or the production area. My model will tackle this complex real-life problem based on this problem. Mathematically, the problem is simpler, but it involves numerous Wells with varied concentrations. We will start by defining the values of our 20 Wells, computing the weighted average, comparing two and three Wells to understand how they operate, and then using MATLAB to graph their relationship. Second, as the model becomes more sophisticated, we will group the Wells into four groups and analyse them to find the best operating combination. We will next utilize our best combination from the analysis to create a process algorithm for our model. Our main goal is to design a process algorithm optimization controller for our model so that the Wells can function at a constant capacity of 16 litre/mins to generate water with 55% average pollution even if one or two Wells are not working at full capacity. The optimization controller will iteratively adjust the Well production capacity until the weighted average pollution level reaches 55%.

Keywords: Optimization; Pollution; Optimization controller; Process Algorithm; Weighted Average; Linear programming

1. INTRODUCTION

Pollution is a worldwide environmental problem that has negative effects on human health as Well as biodiversity and ecosystems. Both natural and human-made processes can be contributors to pollution, which in turn can cause a wide variety of issues for both the environment and human health. Human activity either industrial or residential contaminates water supplies in many countries [1]. Water contamination contributes to the global water deficit because it can't be used for drinking or irrigation. Groundwater is necessary for drinking, irrigation, and industry. Groundwater remediation is aided by optimizing water Well production, especially in areas with many Wells with different pollution levels[2]. The issue requires knowledge of the location's hydrogeology, the pollutants' qualities, and the Wells' operation. The model in this study optimizes water Well production for water cleansing. This model aims to maintain a consistent pollution level in a contaminated groundwater region with (20) Wells with different pollution concentrations. A pharmaceutical firm in Hungary polluted a region by using different chemicals and making different drugs. Remediating the production site's several Wells with different contamination levels is the goal. Our model will solve this complex real-life problem based on this problem. The objective of this study is to develop a model that optimizes the production capacity of the Wells to achieve a constant level of pollution concentration. The proposed model will take into account the varying pollution concentrations of the Wells, their respective production capacities, and the linear constraints inherent in the system. The iterative process employed by the optimization controller will be utilized to modify the production capacity of individual Wells, with the ultimate aim of achieving a weighted average pollution level of 55%. The present research endeavors to make a valuable contribution towards the advancement of a cost-efficient and effective strategy for the remediation of groundwater in regions that have numerous Wells with diverse levels of pollution concentrations.

1.1 Chemical Contamination by Pharmaceutical Companies In Hungary

Reports have emerged in Hungary regarding chemical contamination resulting from the activities of pharmaceutical enterprises, particularly in the water bodies adjacent to their production facilities. The presence of contamination has been detected in certain geographical locations. In the course of their manufacturing operations, these corporations utilize a diverse array of chemicals and compounds. There exists a potential for certain substances to enter the environment, thereby presenting a hazard to both the ecosystem and public health.

In 2018, the Danube Networkers for Europe, an environmental organization based in Hungary, reported that several pharmaceutical companies operating within the country were discharging untreated or inadequately treated wastewater into the Danube River. The Danube River is considered to be a crucial water resource in Hungary. The organization made a claim that the wastewater comprises of compounds that have the potential to be hazardous, such as antibiotics, hormones, and other pharmaceutical residues. These compounds could have adverse impacts on both human health and aquatic ecosystems. [3]

To address chemical contamination from pharmaceutical industries, Hungary needs greater limits and monitoring of their production processes and wastewater discharges. Businesses should use green chemistry and improved wastewater treatment to reduce their environmental impact and improve public health.

1.2 Process Optimization

The act of optimizing a process involves the attainment of its maximum potential with regards to its efficiency, effectiveness, and profitability. The term used to describe this procedure is "process optimization." The achievement of this objective can be realized through a diverse range of techniques, spanning from uncomplicated enhancements in procedures to elaborate modeling and simulation methodologies. The primary aim of optimizing a process is to achieve the highest possible outcome while minimizing the utilization of time, resources, and materials that are expended during the process. Process optimization refers to the utilization of structured methodologies, strategies, disciplines, and tactics to enhance a specific process within the confines of a project or initiative. The optimization of processes has led to a growing need for real-time monitoring of various parameters associated with said processes [4].

Optimization strategies are numerous. Lean Six Sigma, TQM, and other statistical and modeling methodologies are examples. The optimization technique and operating goals will determine the strategy used. Process optimization involves identifying key variables, measuring performance, identifying areas for improvement, and implementing those changes. "Process mapping," "statistical process control," "root cause analysis," and "simulation modeling" are all optimization tools utilized in the optimization of a process [5].

1.3 Importance of the optimized Well production , in case of automated water cleaning process

Within the context of automated water cleaning, the optimization of Well production holds significant significance. This is due to the fact that the extraction rate of water from Wells has an impact on the concentration of pollutants in the water. In the event that the extraction rate surpasses a certain threshold, there exists a likelihood that the purification procedure would be inadequate in eliminating the contaminants, thereby leading to the production of substandard water. Conversely, in the event that the extraction rate is insufficiently high, the cleaning process may not be optimally utilized, leading to a depletion of resources. This issue could potentially be mitigated by augmenting the extraction rate [6].

Optimal Well production ensures that the Wells operate at a constant capacity to generate water with the required pollution level for the automated water cleaning procedure. In this research, the optimization controller will keep pollution at 55% even if one or more Wells are not working at full capacity. Weighted averages will modify each Well's and group's output capability. The weighted average pollution level will linearly constrain this adjustment.

Optimizing Well production ensures that the water cleaning procedure is sustainable and within parameters. The complete

study shows that improving Well production in an automated water cleaning process is necessary to maintain a consistent pollutant concentration and ensure effective and sustainable operation.

2. METHODOLOGY

The materials employed in the development of this study are categorized into two distinct categories, namely resources and tools. The resources comprise of academic and scientific journals, as Well as online resources. The tools utilized include Microsoft Excel, Python, MATLAB software, and TwinCAT PLC automation software.

2.1 Model of the Polluted Ground Water

The proposed model comprises of twenty (20) Wells, each exhibiting varying levels of pollution and distinct water production capacities. A randomized allocation approach was employed to assign pollution concentration levels to individual Wells, ranging from 33% to 75%, aswell as water production capacities between 0.8 liters/min and 2.5 liters/min.

Presented in the following table are the established parameters for the Model, which includes the water production capacity and pollution concentration of each Well.

A formula was derived to calculate the weighted average of the entire contaminated area, which comprises 20 distinct Wells. The formula is derived as follows:

$$y = \frac{\sum_{ij=1}^{n} x_{ikj}}{\sum_{i=1}^{n} x_i}$$
[7].

The formula will be utilized to determine the weighted average of the entire contaminated area, with the aim of ascertaining the consistent level of pollution within the model.

Where:

XiKj= 1966.8 Xi= 34.8. y = 1966.8/34.8 y=56.52%

Table 1: Assigned values for the 20 wells of our model.

Wells	Production Capacity (Liter/mins)Xi	Level Of Pollution Concentration (%)Kj	Xi.Kj
1	0.8	33%	26.4%
2	0.9	36%	32.4%
3	1.2	38%	45.6%
4	1.1	41%	45.1%
5	1.6	45%	72%
6	2.0	51%	102%
7	2.3	62%	142.6%
8	2.5	57%	142.5%
9	2.1	42%	88.2%
10	1.7	68%	115.6%
11	1.8	71%	127.8%
12	1.9	38%	72.2%
13	2.1	44%	92.4%
14	1.0	43%	43%
15	1.3	56%	72.8%
16	1.1	58%	63.8%
17	2.2	69%	151.8%
18	2.3	72%	165.6%
19	2.5	74%	185%
20	2.4	75%	180%
	$\sum Xi = 34.8$		∑XiKj=1966.8

Weighted average: The term "Weighted Average" is also commonly referred to as the "Weighted Mean". The aforementioned is a computation that considers the diverse levels of significance attributed to the numerical values within a given set of data. A weighted average is a statistical measure that assigns different weights to each number in a set, reflecting their relative importance or significance in the calculation of the average value. The nomenclature of the statistical measure suggests its significance [8].

Weighted average is define the formular below:

$$W = \frac{\sum_{i=1}^{n} wix_i}{\sum_{i=1}^{n} wi}$$

W = weighted Average

n = number of terms to be averaged

wi = weight applied to x values

 $Xi = data \ values \ to \ be \ averaged$

The concept of Weighted Average was employed in the derivation of the aforementioned formula for computing the Weighted Average of our model.

2.2 Comparison between two Wells with respect to each other

A comparative analysis was conducted on two Wells to determine their operational characteristics and generate a graphical representation using MATLAB.

Here, we utilized Well 1 and Well 20 as sources of data.

We will use Well 1 and Well 20

Well 1 = 0.8 liter/mins and 33%

Well 20-2.4 liter/mins and 75%

The formula utilized is $y = \frac{\sum_{ij=1}^{n} x_i \kappa_j}{\sum_{i=1}^{n} x_i}$ [7]

$$y = \frac{(0.8 * 0.33) + (2.4 * 0.75)}{(0.8 + 2.4)} \quad y = \frac{2.064}{3.2}$$

y = 0.645 - 64.5%

Thus, the weighted average obtained from Well 1 and Well 20 is 64.5% when weighted by their respective contributions.

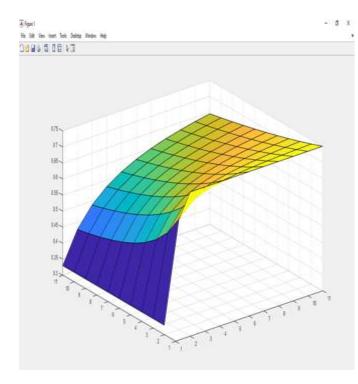


Fig 1 : Visualization of Well 1 and Well 20 relationships.

The diagram presented above illustrates the interdependence of Well 1 and Well 20, depicting their operational dynamics in relation to one another.

2.3 Comparison between three Wells with respect to each other

Here, a comparison was made among three Wells to determine their operational characteristics relative to one another. However, the visualization of the resulting graph depicting the performance of these Three (3) Wells on MATLAB was found to be challenging and arduous.

Here, we utilized Well 1, Well 10, and Well 20.

Well 1 –(0.8 liter/mins & 33%), Well 10 – (1.7 liter/mins & 68%) and Well 20 – (2.4 liter/mins & 75%)

Using
$$y = \frac{\sum_{i=1}^{n} x_i \kappa_j}{\sum_{i=1}^{n} x_i}$$
 [7]
 $y = \frac{(0.8 * 0.33) + (1.7 * 0.68) + (2.4 * 0.75)}{(0.8 + 1.7 + 2.4)}$
 $y = \frac{3.22}{4.9}$
 $y = 0.657 _ 65.7\%$

Thus, the calculated weighted average of Well 1, Well 10, and Well 20 is 65.7%. Visualizing the graph of the three (3) Wells becomes challenging when dealing with more than two Wells, as the model complexity increases when working with three or more Wells. The proposed approach involves the grouping of Wells to facilitate the operationalization of the model.

2.4 Grouped Data

Production Capacity	Level Of Pollution			
[Xi] (Liter/mins)	Concentration [Kj] (%)			
Group 1				
0.8+0.9+1.2+1.9+1.1+2.1+1.0	33%, 36%, 38%, 38%, 41%, 42%, 43%			
Sum= 9 liter/mins	Group Avg= 38.71%. Weighted Avg=39.21%			
Group 2				
2.1+1.6+2.0	44%, 45%, 51%			
Sum= 5.7 liter/mins	Group Avg= 46.67%. Weighted Avg=46.74%			
Group 3				
1.3+2.5+1.1+2.3	56%, 57%, 58%, 62%			
Sum= 7.2 liter/mins	Group Avg= 58.25%. Weighted Avg=58.57%			
Group 4				
1.7+2.2+1.8+2.3+2.5+2.4	68%, 69%, 71%, 72%, 74%, 75%			
Sum= 12.9 liter/mins	Group Avg= 71.5%. Weighted Avg=71.77%			

The contaminated area comprises of a total of 20 wells exhibiting varying degrees of pollution. Managing a set of 20 wells presents a complex and challenging task in achieving a consistent level of pollution control. Due to the intricate nature of the data, we opted to categorize the wells into four distinct groups based on their pollution levels' similarity. This approach was taken to streamline the model and facilitate calibration and manipulation.

2.5 Finding the best possible Combination to operate on

The collective maximum performance of the 20 wells is 34.8 liters per minute. However, it is preferred to operate the model at a capacity lower than the maximum to allow for greater flexibility in addressing potential issues or errors. Therefore, it is recommended to operate the model at no more than half of the maximum capacity of the wells. Utilizing the model at a reduced capacity in comparison to its maximum water production capability would afford us greater flexibility in experimenting with various combinations. Determining the optimal combination for operation will provide greater latitude and understanding regarding the optimal value at which our model will function and produce the intended output. The task at hand necessitates the examination of three distinct data sets to authenticate and corroborate the hypotheses under scrutiny. In order to identify the optimal combination for operation, a sample of 1000 random numbers

was generated. Each number in the sample consisted of four distinct random digits, with the constraint that the sum of these digits equaled 16. The maximum capacity of each group was taken into consideration during the generation process. The experiment was conducted thrice, resulting in three distinct datasets. The purpose of this analysis was to confirm our hypothesis regarding the identification of the optimal combination for operate upon.

	First Dataset	Second Dataset	Third Dataset
Min Weighted Avg	44.42%	44.66%	44.13%
Max Weighted Avg	69.68%	70.17%	70.28%
Difference	25.25	25.50	26.15
WA Range with highest Combination	50-58%	50-60%	50-58%

Table 3: Analysis of the three distinct dataset generated.

The primary objective of this study is to develop a process optimization controller for our model, aimed at achieving a consistent level of production capacity of 16 liters per minute across all wells, while maintaining an average pollution level of 55%. This optimization controller will be designed to accommodate scenarios where one or more wells may not be operating at full capacity. Additionally, the study aims to determine the maximum limit of the optimization controller in optimizing water production in situations where multiple wells are not functioning at full capacity.

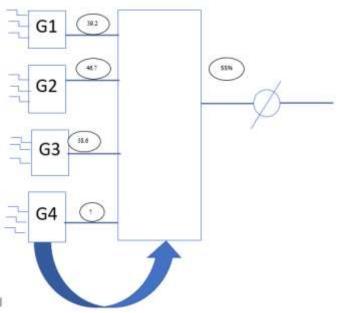


Fig 2 : Process Optimization of the model.

Optimal Interval is 50-60% = 55% Avg.

3. RESULT

The concept of linear programming constitutes the basis for the creation of the optimization controller. The optimization controller employs an iterative approach to modify the production capacity of individual wells, with the aim of achieving a targeted value of 55% for the total weighted average pollution level.

The iterative methodology bears resemblance to the simplex algorithm, which is commonly employed in linear programming to determine the optimal solution for a linearly constrained linear programming problem.

One of the optimization controller's tasks was to compare the pollution level of the well with the weighted average pollution level, with the aim of optimizing the pollution amount to 55% of the average. If such a scenario arises, the output capability of the well is enhanced by the quotient of the cumulative weighted average contamination level and the contamination level specific to the well.

Consequently, the optimization controller modifies the production capacity of individual wells to maintain a consistent pollution level of 55%. The aforementioned task is achieved through the utilization of a weighted average methodology that considers both the output potential of individual wells and the level of contamination generated by each cluster of wells. Upon completion of this process, it guarantees the optimization of production capacity while concurrently minimizing the degree of pollution.

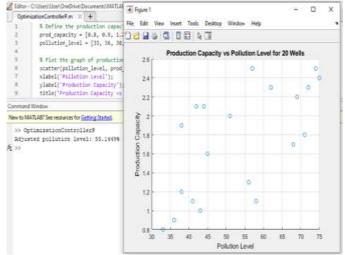


Fig 3: The optimization controller optimizing the assigned values of the model at 55% Average Pollution level [9].

The figure above shows the optimization controller developed in MATLAB optimizing the model's original assigned values to give us the desired target pollution of 55% average. The model has been optimized to operate at a constant capacity of 16 liter/mins to produce water with 55% average pollution.

The optimized model plots the relationship between each well's production capacity and pollution level at 16 liter/mins to produce water with 55% average pollution. Our model produces 0.8-2.5 liters/minute and pollutes 33%-75%.

3.1 Comparison of the Optimization Controller while Working at a Less Capacity

We will compare and analyze the optimization controller's behavior when one, two, or more wells are not working at full capacity and determine the threshold of production capacity reduction beyond which the system can optimize water production while maintaining a constant level of 16 liters per minute and an average pollution level of 55%.

Table 4 : Summary of	f Wells	Production	Capacity	and its
Optimized result.				

S/N	Reduced Well(s)	Optimization Result
1	0 Well Reduction	55%
2	1 Well Reduction	55.4554%
3	2 Wells Reduction	55.6614%
4	3 Wells Reduction	55.7865%
5	4 Wells Reduction	55.9987%
6	5 Wells Reduction	56.1587%
7	6 Wells Reduction	56.4194%
8	7 Wells Reduction	56.4292%
9	8 Wells Reduction	56.666%

The optimization controller can only optimize water production to 55% average pollution when four of the twenty wells have their water production capacity reduced to a lesser capacity. When five or more wells are reduced, the optimization controller cannot optimize production capacity at the stipulated 55% pollution average, as we saw in our analysis. After reducing Four Wells, our Twenty Wells' overall output capacity dropped to 33.5liter/minute from our model's 34.8liter/minute. The Optimization controller optimized the outcome to 55% pollution level average at 33.5liter/minute, the same as at 34.8liter/minute.

3.2 Production Capacity Generator

A code generator was developed to generate random values for our model's Production Capacity to determine and analyze our optimization controller's efficiency in optimizing water production to an average pollution level of 55% even if one or more wells are not working at full capacity of our model's assigned values.

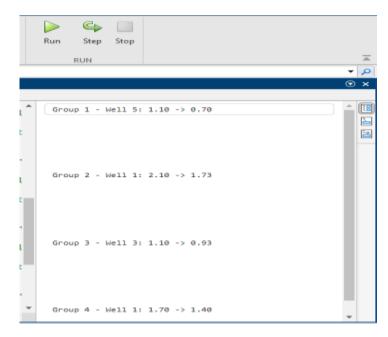


Fig 4 : New Production Capacity value Generator [9].

4. CONCLUSION

In conclusion, the study has presented a model for optimizing water wells production for a water cleaning process in a reallife scenario where an area was contaminated by a pharmaceutical company's production activities. The model was based on linear programming principles and involved finding the optimal solution to adjust the production capacity of each well to maintain a constant pollution level of 55% given the initial production capacity and pollution level of each well. The optimization controller used a weighted average approach that takes into account the production capacity and pollution level of each well and each group of wells. The limit of the optimization controller was found to be reducing the water production capacity of four wells, beyond which it was unable to optimize the production capacity at the stipulated 55% pollution average. Overall, the study's model can be useful in optimizing water production for cleaning processes in contaminated areas with multiple wells of different pollution concentrations. Subsequent to this study, the forthcoming endeavors will encompass the deployment of the optimization controller onto a designated Programmable Logic Controller (PLC) via Twincat programming. The implementation of this technology will enable the automation of water purification in real-time. Further testing and validation are necessary for the optimization controller, utilizing data obtained directly from the site affected by the corporation's contamination. Upon completion of simulated testing, the optimization controller is expected to be implemented in practical applications.

5. REFERENCES

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