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Using of a Fuzzy Logic as One of The Artificial Intelligence Models to Increase the Efficiency of The Biological Treatment Ponds in Wastewater Treatment Plants

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Abstract: One of the most essential variables in water quality management and planning appears to be biological treatment in wastewater treatment plants. This critical characteristic, however, is difficult to measure and takes a long time to produce accurate findings. Scientists have attempted to develop several strategies to solve these challenges. Artificial intelligence models are one such way it is feasible to monitor the treatment plants pollutant parameters and manage these pollution elements during processing more reliably and economically. The use of a fuzzy logic model to control biological wastewater treatment is proposed in this research. The objective of these software models is to predict future treatment problems, intervene in the facility quickly and effectively, reduce or eliminate environmental pollution, improve the ecosystem, and determine the treatment efficiency of the wastewater treatment plant by using fewer laboratory-scale reactors and pilot plants. This study aims to use artificial intelligence models (fuzzy logic model) to achieve the best biological treatment (BOD, TN and TP) while at the same time ensuring that the treated wastewater is within the standards. The model was generated using FL (MATLAB software was used to create the FL model), and the model inputs are HRT, pH, temperature, F/M and BOD load to assess to which degree each of these variables affects BOD, TN and TP. The model outputs were within the acceptable wastewater quality standards according to the Turkish water pollution control regulation for the receiving environment of treated wastewater.
Keywords: Biological treatment, artificial intelligence models, fuzzy logic, treated wastewater, Biological Oxygen Demand, total nitrogen and total phosphorus.

INTRODUCTION

The operation of wastewater treatment plants is influenced by a number of unknown variables. These include the physical and chemical features of wastewater streams, as well as biological processes' degradation mechanisms. Improved process control algorithms based on artificial intelligence technologies have garnered a lot of attention as a result of escalating environmental and economic concerns. Recent advances in control engineering suggest that hybrid control strategies, integrating some ideas and paradigms existing in different soft computing techniques, such as fuzzy logic, genetic algorithms, and neural networks, may provide improved control of effluent quality [1].

Fuzzy logic (FL) is a powerful methodology for solving problems with many applications in control and information processing. The use of a fuzzy controller has significantly changed the approach to control problems. Conventional controllers adjust the control sizes of the system based on a set of differential equations that represent a model of a dynamic system. In fuzzy controllers, the control values are obtained based on fuzzy rules, which are similar to the model of human reasoning. It is difficult to achieve treatment efficiency in wastewater treatment systems under dynamic loading situations. Process control could be a valuable tool to minimize both environmental and economic impacts because the operation of a wastewater treatment process is intimately linked to wastewater sources, chemical composition, flow rate, biological process conditions, and the recycle ratio of the settled sludge.[2].

Soft computing tools such as FL-based methods, neural networks, and genetic algorithms have had major and expanding impacts over the last few decades. However, in environmental domains such as risk assessment, cost-benefit analysis, and life-cycle impact assessment, these methodologies have only been used in a limited way. It's impossible to say how much of an influence fuzzy approaches will have on environmental policies in the coming decades because they provide both fresh opportunities and unexpected issues as compared to current methods.[3].

For the types of complex and imprecise problems that arise in environmental policy, the ability to model complex behaviors as a collection of simple if-then rules makes fuzzy logic an appropriate

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modeling tool. Because fuzzy arithmetic works well for addressing linguistic variables and poorly characterized parameters, fuzzy methods offer the opportunity to evaluate and communicate assessments based on linguistic terms that could match those of the public and decision-makers. Moreover, approximate reasoning methods such as fuzzy arithmetic do not require well-characterized statistical distributions as inputs. Another key advantage of fuzzy logic in risk assessment is the ability to merge multiple objectives with different values and meanings, for example combining health objectives with esthetic objectives. It also provides rules for combining qualitative with quantitative objectives. But we must recognize and confront the potential limitations of fuzzy logic for expressing health risk and other environmental impacts [1].

Researchers frequently fail to make precise statements about inputs and outcomes when modeling complex environmental problems, but fuzzy logic could be applied to the development of environment indices in a way that solves several common problems, such as observation incompatibility and the need for implicit value judgments.

Since the 1970s, studies concentrating on biological treatment systems in wastewater treatment plants have been carried out. The effect of pH on the efficiency of biological treatment ponds for industrial wastewater was studied using fuzzy logic [4]. The fuzzy logic model was used to find the most mature option for low head hydropower technology at the outlet of wastewater treatment plants by evaluating relevant economic, technical and environmental parameters [5]. On the other hand, the actual control of the aeration process in the biological treatment stages was studied, which is an energy-consuming process, and by using the fuzzy logic model, dynamics were found to reduce the energy use in the aeration process [6]. The fuzzy model was also used in deciding to choose the appropriate treatment technologies in biological treatment ponds by evaluating four treatment methods: Anaerobic Anoxic Oxic, Triple Oxidation Ditch, Anaerobic Single Oxidation Ditch, Sequencing Batch Reactor Activated Sludge [7].

The fuzzy model also helped to reveal whether it was possible to reuse the treated wastewater to meet the requirements of its reuse in the agricultural and industrial fields [8].

This research aims to use artificial intelligence models (fuzzy logic) to achieve higher efficiency for the work of biological treatment ponds in wastewater treatment plants by studying the effect of some variables (temperature, PH, hydraulic retention time, F/M and BOD load) on the level of total nitrogen, total phosphorous and biological oxygen demand, at the same time making sure that the treated wastewater is within Acceptable standards according to the reception environment.

MATERIALS AND METHODS

Mamdani was the first to establish fuzzy logic models (also known as linguistic models or fuzzy if-then rules) based on Zadeh's idea of fuzzy sets. These models are capable of dealing with very unpredictable systems.[9]. The theory of fuzzy sets, initially introduced by Zadeh in 1965, is a valuable technique of capturing data uncertainty and imprecision without the use of complex mathematical equations. These models have the advantage of being able to model non-linear functions in a simple and understandable manner by describing the reasoning in terms of language rather than numerical values. In the form of fuzzy rules, they provide a valuable technique to describe human knowledge in a legible way [10].

Fuzzy Controllers

Fuzzy controllers are conceptually quite simple. They are made up of three stages: input, processing, and output. Sensor or other inputs, such as switches, thumbwheels, and so on, are mapped to the proper membership functions and truth values in the input stage. The processing stage calls each relevant rule and generates a result for each, before combining the results. Finally, in the output stage, the combined result is converted back into a specified control output value[11]. Although trapezoidal and bell curves are also employed, the shape of membership functions is less significant than the number of curves and their arrangement. To span, the required range of an input value, or the "universe of discourse" in fuzzy language, three to seven curves are often acceptable. As discussed earlier, the processing stage is based on a collection of logic rules in the form of IF-THEN statements, where the IF part is called the "antecedent" and the THEN part is called the "consequent". Typical fuzzy control systems have dozens of rules[12]. Fuzzy control system design is based on empirical methods, basically, a methodical approach to trial-and-error as shown in figure (1).

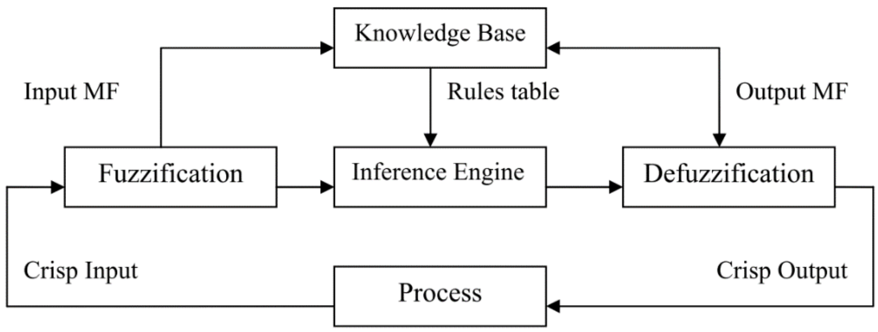


Figure 1. Basic Structure of the Fuzzy Logic Controller

Applications of Fuzzy Logic

A fuzzy set can be simply defined as a set with fuzzy boundaries. Let X be the universe of discourse and its elements be denoted as x. In classical set theory, crisp set A of X is defined as function $f_A(x)$ called the characteristic function of A

$$f_A(x): X \to 0\,,1\,, \qquad (1)$$

where

$$f_A(x) = \begin{cases} 1, & if\ \ x \in A \\ 0, & if\ \ x \notin A \end{cases}$$

This set maps universe X to a set of two elements. For any element x of universe X, characteristic function $f_A(x)$ is equal to 1 if x is an element of set A, and is equal to 0 if x is not an element of A. In the fuzzy theory, fuzzy set A of universe X is defined by function $\mu_A(x)$ called the membership function of set A

$$\mu_A(x): X \ \to [0\ 1], \qquad (2)$$

where

$\mu_A(x) = 1\ if\ x\ is\ totally\ in\ A;$
$\mu_A(x) = 0\ \ if\ x\ is\ not\ in\ A;$
$0 < \mu_A(x) < 1\ if\ x\ is\ partly\ in\ A.$

This set allows a continuum of possible choices. For any element x of universe X, membership function $\mu_A(x)$ equals the degree to which x is an element of set A. This degree, a value between 0 and 1, represents the degree of membership, also called membership value, of element x in set A[13].

In this study, the fuzzy logical formalism was used to access treated wastewater according to the standards of the receiving environment by developing a water quality index. Studying some factors affecting biological treatment ponds based on fuzzy logic. Fuzzy inference is the process of formulating mapping from a given input determinant to an output determinant using fuzzy logical reasoning. Decisions can be made based on mapping or identifying patterns. The fuzzy inference process includes three critical steps: membership functions, fuzzy group operations, and inference rules. The model was evaluated with data according to the specifications of raw wastewater and compared to the specification table for treated wastewater classified into four classes according to the quality of treated wastewater in Turkey as shown in table (1) based on the Mamdani fuzzy inference system by using MATLAB.

Table 1. Water pollution control regulation (Official newspaper Date: 31.12.2004 Official newspaper Number: 25687)

Parameters	WATER QUALITY CLASSES			
	I	II	III	IV
BOD (mg/L)	4	8	20	> 20
KOD (mg/L)	25	50	70	> 70
TN (mg N/L)	0.5	1.5	5	> 5
TP (mg P/L)	0.02	0.16	0.65	> 0.65
FC (EMS/100 mL)	10	200	2000	> 2000
TC (EMS/100 mL)	100	20000	100000	> 100000
DO (mg O2/L)	8	6	3	<3
TOC (mg/L)	5	8	12	> 12
PH	6.5-8.5	6.5-8.5	6.0-9.0	Out of 6.0-9.0
Temperature (^{o}C)	25	25	30	> 30

The most efficient architecture was chosen as the final model for predicting the effluent BOD, TN and TF concentrations. This model has 5 inputs variables: HRT, temperature, PH , F/M and BOD Load with 3 membership functions associated with each input as illustrated in Figure (2) and Figure (3) show the Gaussian membership functions on the operating range. Table (2) shows the parameters of the Gaussian membership functions associated with the input variables, where c is the center of the corresponding membership function and b is the width. The model contains 197 rules.

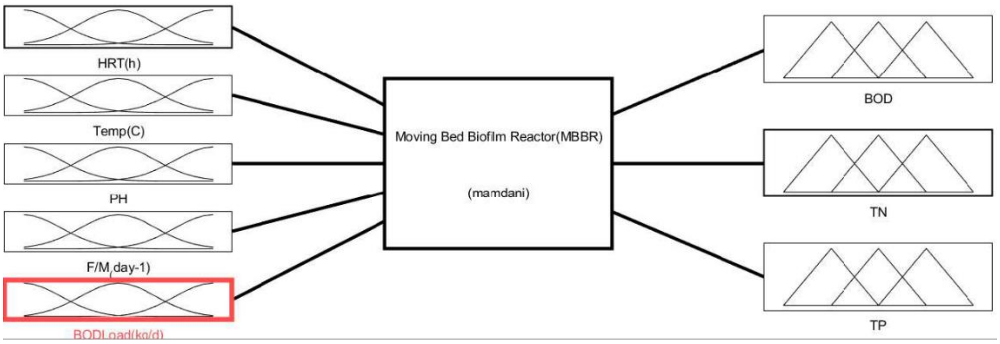


Figure 2. The structure of the fuzzy logic model

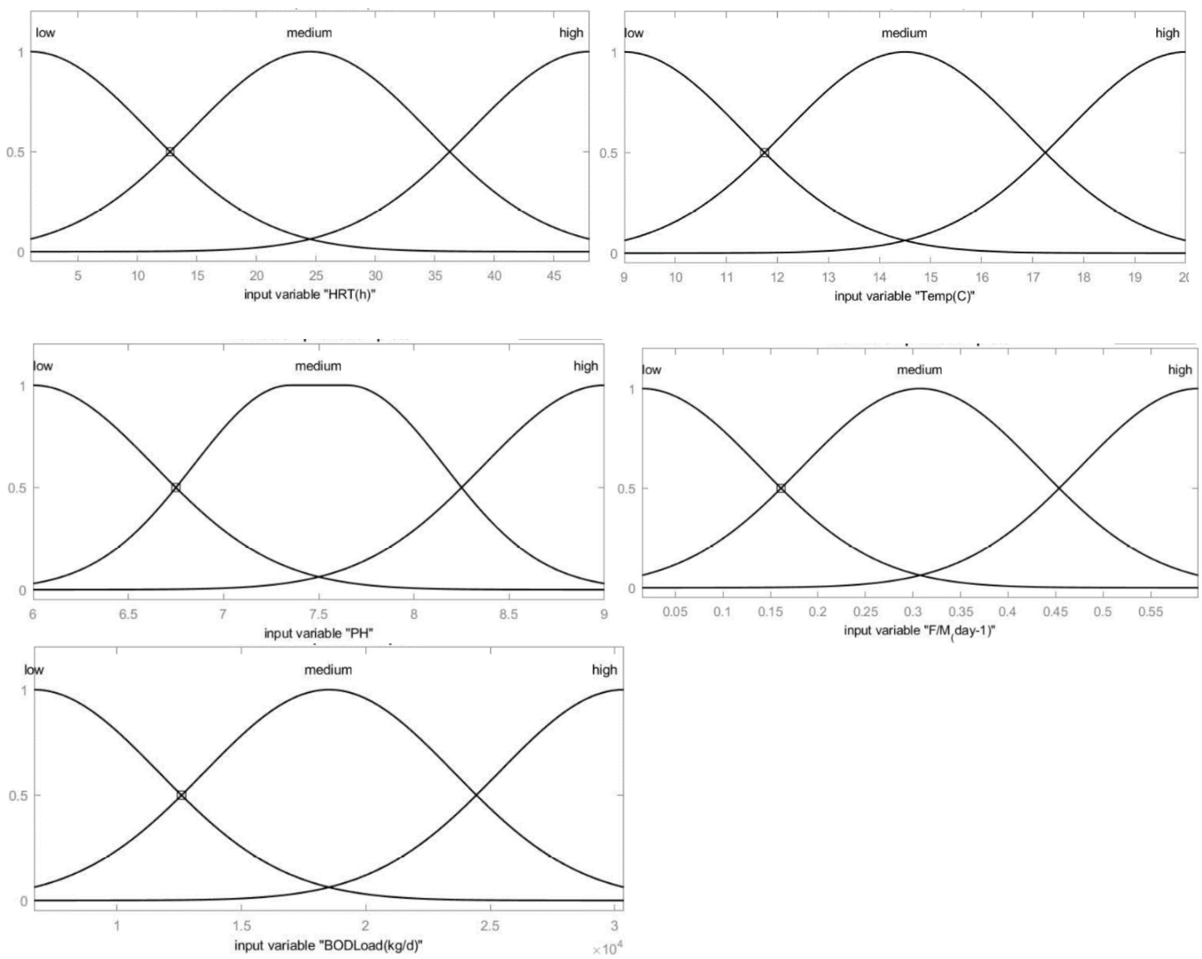


Figure 3. Fuzzy membership functions in the input space.

Table 2. The parameters of Gaussian membership functions associated with the

Inputs	Membership Function	b (Width)	C (Centre)
HRT	low	9.98	1.00
	medium	9.98	24.50
	high	9.98	48.00
Temp	low	2.336	9.00
	medium	2.336	14.50
	high	2.336	20.00
PH	low	0.637	6.00
	medium	0.5096	7.35 and 7.65
	high	0.637	9.00
F/M	low	0.1242	0.02
	medium	0.1242	0.31
	high	0.1242	0.60
BOD Load	low	5030	6670.00
	medium	5030	18510.00
	high	5030	30360.00

The example of optimal fuzzy rules obtained using the modeling technique described in this study is shown in Table (3). The number of rules was 197 and the aggregation process is illustrated in Figure (4). Each rule listed in the table consists of an IF and THEN part. The IF part specifies a set of conditions and the THEN part specifies the conclusion of the action. For example, rule 10 in Table (3) can be read as: IF (HRT) is Low and (Temp) is Medium and (PH) is Low, THEN (effluent BOD) is high and (effluent TN) is high and (effluent TP) is high. Another example illustrates Figure (4) can be read as: IF

(HRT) is 24.5 h and (Temp) is 17.6 oC and (PH) is 7.36 and (F/M) is 0.307 day-1 and (BOD load) is 18500kg/day, THEN (effluent BOD) is 22.8mg/l and (effluent TN) is 4.37mg/l and (effluent TP) is 0.338mg/l.

Table 3. optimized fuzzy rules(30ruls as an example) generated using the modeling strategy developed in this study

Rule No.	Rule Antecedent (If) (and)					Then		
	HRT	Temp	PH	F/M	BOD Load	BOD	TN	TP
	hour	C		Day $^{-1}$	Kg/d	mg/l	mg/l	mg/l
1	Low	low	none	none	none	high	high	high
2	low	medium	none	none	none	high	high	high
3	low	high	none	none	none	medium	medium	medium
4	medium	medium	none	none	none	medium	medium	medium
5	medium	high	none	none	none	low	low	low
6	high	high	none	none	none	low	low	low
7	low	low	low	none	none	high	high	high
8	low	low	medium	none	none	high	high	high
9	low	low	high	none	none	high	high	high
10	low	medium	low	none	none	high	high	high
11	low	medium	medium	none	none	medium	medium	medium
12	low	medium	high	none	none	high	high	high
13	low	high	low	none	none	medium	medium	medium
14	low	high	medium	none	none	medium	medium	medium
15	low	high	high	none	none	medium	medium	medium
16	medium	low	low	none	none	high	high	high
17	medium	low	medium	none	none	medium	medium	medium
18	medium	low	high	none	none	high	high	high
19	medium	medium	low	none	none	medium	medium	medium
20	medium	medium	medium	none	none	medium	medium	medium
21	medium	medium	high	none	none	medium	medium	medium
22	medium	high	low	none	none	medium	medium	medium
23	medium	high	medium	none	none	low	low	low
24	medium	high	high	none	none	medium	medium	medium
25	high	low	low	none	none	medium	medium	medium
26	high	low	medium	none	none	low	low	low
27	high	low	high	none	none	medium	medium	medium
28	high	medium	low	none	none	medium	medium	medium
29	high	medium	medium	none	none	low	low	low
30	high	medium	high	none	none	medium	medium	medium

Figure 4. Fuzzy inference diagram for the model predicting effluents the user just needs to put the input values to get the output value as seen from the figure.

RESULTS AND DISCUSSION

The treated wastewater quality for the moving bed biofilm reactor as an example of aeration ponds has been assessed with the water pollution control regulation (Turkey). The calculated indices according to the fuzzy inference system (FIS) are given in (Fig. 2). On the other hand, a comparison has been done between the fuzzy logic model and the water pollution control regulation index.

The results of the fuzzy logic model, that is, the treated wastewater(BOD,TN and TP) according to the model, were compared with the Turkish Water Pollution Control Regulation to be safely disposed of in the receiving environment

The observations of fuzzy model testing are shown in (Fig. 4). In the fuzzy model, BOD,TN and TP are showing acceptable and are mainly affected by HRT, Temp, PH, F/M and BOD load values as shown in figure (5). Figure (6 and 7) illustrates the effect of each of the previously mentioned factors on the TN and TP.

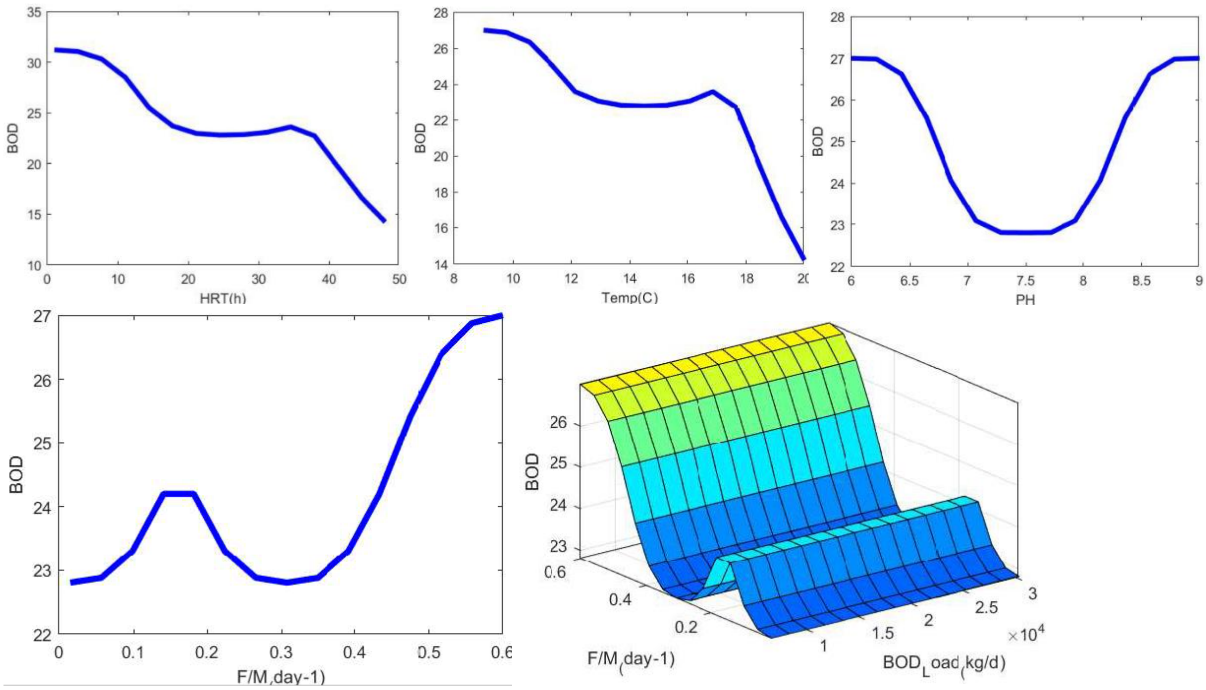
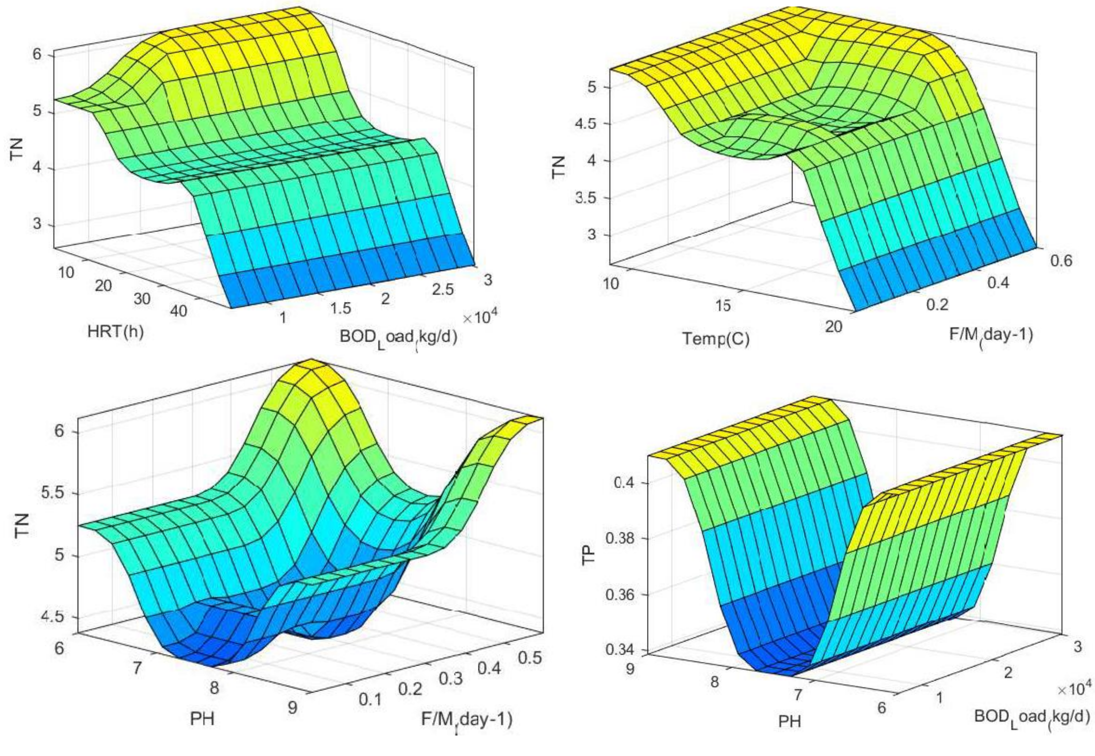


Figure 5. The effect of different variables (HRT, Temp, PH, F / M and BOD load) on BOD.



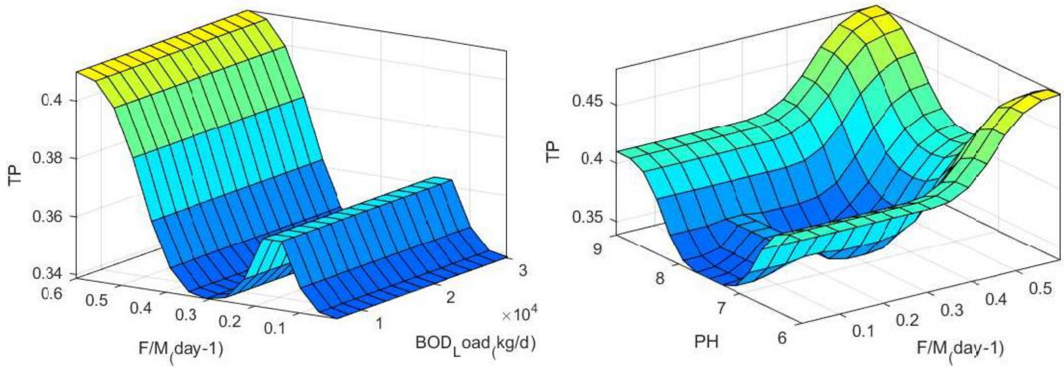


Figure 6. The effect of different variables (HRT, Temp, PH, F/M and BOD load)on TN and TP.

CONCLUSIONS

Modeling the moving bed biofilm reactor (MBBR)(Biological Treatment) can improve the performance of wastewater treatment plants and may lead to a better comprehension of the system. However, the complexity and uncertainty in the process make the task somewhat complicated using traditional deterministic models. Another set of modeling tools known as artificial intelligence or data-driven techniques exist that do not require prior knowledge of the system's structure or state. The quality of these procedures, on the other hand, is heavily reliant on the data quality.

Artificial intelligence models, particularly fuzzy logic models, have the advantage of being able to anticipate effluent concentrations without prior knowledge of the system. Furthermore, there are no assumptions about the mathematical relationships between inputs and outputs. Furthermore, without explicitly considering the physics of the process, these models may recognize the links between the inputs and outcomes. The main aim of this research work was to test the hypothesis that artificial intelligence techniques can be used for modeling the moving bed biofilm reactor wastewater treatment plants. Consequently, the objectives of this study were to investigate the efficiency of FL model in improving the data-driven techniques developed in this study. Other objectives were also inherent in this project, namely preparation of the data to eliminate the effect of noise and missing values and developing a software sensor to predict the BOD, TN and TP.

The fuzzy logic model (Mamdani) was satisfactory and within the required specifications for treated wastewater according to the classifications of Turkish water pollution control regulation for the receiving environment of treated wastewater.

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