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Decision-making support for optimizing pollutant degradation processes in domestic wastewater treatment plants involving uncertain parameters via fuzzy programming approaches

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Abstract. A fuzzy optimization model was implemented in this study as a decision-making approach to optimize pollutant degradation processes in facultative ponds of domestic wastewater treatment plants. The fuzzy parameters are due to uncertain situations, which eliminate the need for managers to collect data, particularly when the data are no longer represent the real situation. The managers formulate the fuzzy parameters in the problem based on their intuition and experience in using the provided decision-making tool. Also, the fuzzy optimization model proposed in this study was solved using the fuzzy-based programming approach with the generalized gradient algorithm performed in LINGO 19.0 optimization software. In addition, the numerical experiment was conducted with secondary and generated data for the certain and fuzzy parameters, respectively. The results showed that optimal decisions were achieved and the manager can then use the proposed model in managing domestic wastewater treatment plants.

Keywords: Domestic wastewater / facultative pond / pollutant degradation / fuzzy programming / wastewater treatment plant

1 Introduction

Wastewater treatment is one of the most important issues in the world in biotechnology [1]. Wastewater treatment plants reduce pollutant before it is disposed to nature or reused in which biological and chemical processes via storing wastewater in ponds are a common approach in operating wastewater treatment plants [2]. Figure 1 indicated structures used in this approach, which showed a wastewater treatment plant employed in Yogyakarta, Indonesia, which is the object of this study. There are various processes involved in the plant, with the most significant occurring in facultative ponds, where the pollutant is degraded by bacteria, algae, and zooplankton [3]. The facultative ponds have a limited capacity to store wastewater, and the more wastewater contained in a pond, the longer it takes to remove the pollutant. Hence, filling a pond to half its capacity will take a shorter time in reducing the pollutant concentration than the maximal quantity. Therefore, the managers need decision-making support in determining the amount of wastewater to be pumped into facultative ponds and the processing time to ensure that the pollutant concentration is close to the desired value, known as the treatment's performance.

A variety of schemes have been proposed to analyses the performance of wastewater treatment plants. This involved the use of quantitative approaches such as the pollutant degradation coefficient analysis against the flow velocity [4], analysis of the effectiveness and purification of the biological oxygen demand concentration [5], and a natural adsorbent approach in wastewater processes [6].

Meanwhile, other approaches involved mathematical model-based analysis, such as linear programming [7]. Some studies were conducted on various aspects such as sewage treatment [8], the recycling of sedimentation from wastewater treatment ponds for energy and environmental impact mitigation [9], and the reuse of wastewater residue for bricks and recycled-water [10]. Furthermore, distinctive studies on optimizing the performance of wastewater treatment plants have been reported, such as an integrated approach based on hydraulic and physio-chemical-biological models [11], mathematical optimization-based approaches [12–15], and a molecular approach [16]. These models only apply to certain environments, where all parameter values are known with certainty. However, a few

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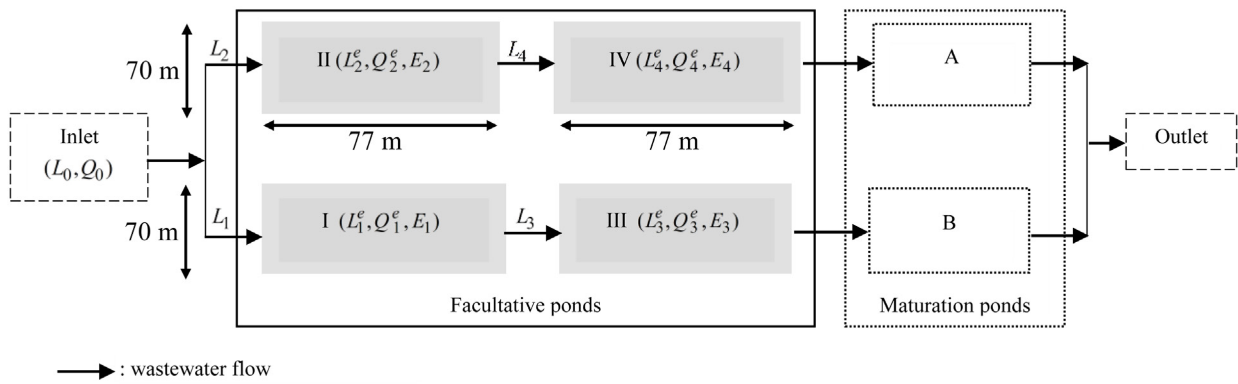

Fig. 1. A wastewater treatment plant in Yogyakarta, Indonesia, cf. [30].

parameters may be unknown and uncertain in practices, hence methods that can handle these uncertainties are required.

The uncertainty theory is commonly used to solve decision-making problems containing uncertain parameters from mathematical perspectives. For optimization problems, probabilistic programming models are used as decision-making tools in optimizing fiber reinforced polymer matters [17], optimizing energy hub plants [18], and radiotherapy dose optimization [19]. Nevertheless, probabilistic programming requires historical or experimental data for the corresponding parameters. Fuzzy programming is used for unavailable data. This approach represents uncertain parameters as fuzzy variables with membership functions defined by managers. Fuzzy programming models have been reported as a powerful tool in decision-making problems in various fields, such as photovoltaic panel designs [20], energy or power management [21–24], supply chain management [25–28], advanced manufacturing processes [29], and many more.

Based on our knowledge, there is no existing models that can be used as a decision-making support in wastewater treatment plants containing fuzzy parameters, and particularly for multi-period of observations; these are the main urgencies of the study. This motivates us to propose a fuzzy programming model in this study, which can be used as decision-making support for wastewater treatment optimization with multiple review periods. The model was formulated in fuzzy quadratic programming. The term fuzzy refers to the fact that some fuzzy parameters were involved in the problem. Meanwhile, the quadratic term comes from the objective function which is a quadratic function of the difference between the pollutant degradation efficiency index values and their reference values decided by managers; this was formulated as an attempt to bring the actual values close to their reference, and the quadratic form was used to guarantee that the proposed optimization model is always well-defined, i.e., solvable, see also the forthcoming mathematical model formulation in Section 3. Moreover, a numerical experiment result was observed to study the implementation of the proposed approach.

2 Materials and methods

Wastewater treatment plants commonly consist of inlet parts to filter physical matters, facultative ponds, maturation ponds, and outlet parts. Figure 1 shows the layout of the Sewon wastewater treatment plant located in Yogyakarta, Indonesia; this is the object of the study, and the mathematical model is built based on this layout. The main process of pollutant degradation occurs in facultative ponds, where natural processes such as chemical and biological processes are employed to reduce the pollutant concentration in the wastewater. Then, the study focuses only on facultative ponds, and the processes in the maturation ponds are excluded; this is the limitation of this study.

The mathematical notations in Figure 1 are explained in Table 1. The mathematical optimization model works under the following specifications: (1) the biological oxygen demand's degradation rate, the wastewater amount, and load before entering facultative ponds are the three fuzzy variables involved in the problem (2) there are unavailable data to represent the fuzzy variables, or the data are not reflecting the real situation due to unusual weather or structural changes (3) managers formulate the fuzzy variable membership functions based on their intuition and experience (4) the values of certain parameters are obtained from previous studies collected in a wastewater treatment plant in Yogyakarta, Indonesia (5) the value for the upper bound of the pollutant concentration that is safe to dispose is based on the Yogyakarta province government policy, which is 50 mg/L of the biological oxygen demand's concentration [31] (6) managers maximize the amount of wastewater processed on each facultative pond and (7) managers want to track desired values using an efficiency index of each facultative pond, hence, minimizing the difference between the real efficiency index values and their references will be considered in the objective function.

Meanwhile, there are three assumptions employed in the model, namely (1) one periodic review time equals one day, without loss of generality. However, it could be hourly, daily, weekly, etc., in practice, and (2) according to the layout in Figure 1, the wastewater load processed on ponds III and IV is half of those on ponds I and II, and (3) all fuzzy membership functions have discrete membership forms.

Table 1. Mathematical notations.

Notations	Units	Explanation
i	NA	Index of the facultative pond
k	[day]	index of periodic review time instant, without loss of generality, we assume one periodic review time to be one day;
$L_i^e(k)$	[kg]	The amount of wastewater entering the facultative pond i (kg/) at the periodic review time *k;*
$t_i(k)$	[day]	Duration of the wastewater processing on the facultative pond i at the periodic review time k.
$C_i(k)$	[mg/L]	The concentration of the biological oxygen demand in the wastewater that processed on the facultative pond i at the periodic review time k;
$E_i(k)$	[%]	The efficiency index value of the treatment on the facultative pond i at the periodic review time k;
BM	[mg/L]	The upper bound of the concentration of the biological oxygen demand in the processed wastewater before leaving the facultative ponds;
$\tilde{Q}_i^e(k)$	[m3/day]	A fuzzy variable which represents the wastewater amount before entering the facultative pond i at the periodic review time k;
$\tilde{L}_i(k)$	[kg/day]	A fuzzy variable that represents the wastewater load before entering the facultative pond i at the periodic review time k;
$\tilde{k}(k)$	[%]	A fuzzy variable that represents the biological oxygen demand's degradation rate at the periodic review time k.

The methodology adopted in this study is explained in the following problem solving steps/descriptions, see also Figure 2 for illustration. First, the wastewater treatment plant's layout has been specified in Figure 1. The proposed mathematical model is based on this layout. The flow of wastewater follows the direction illustrated in Figure 1. Three fuzzy parameters are already introduced in Table 1. Those three fuzzy parameters are motivated by the situation in which historical data are not available, or, data are available however it does not describe the current situation. In this case, managers provide the fuzzy membership function for each fuzzy parameter. Next, managers collect the data for certain and known parameter values and formulate membership functions for the fuzzy variables, see the forthcoming Section 4.1 for more technical details. Two decision variables for each facultative pond were determined using a mathematical optimization model formulated in the next section of this study. These decision variables include the processed wastewater amount on each facultative pond and the processing duration based on the pollutant degradation rate, where the pollutant concentration is lower than the upper bound value. After that, a mathematical optimization model containing fuzzy variables was developed with two objective functions, and various constraints are included in the model, see Section 3 for further explanation. Then, the LINGO 19.0 optimization software is used to solve the derived optimization problem. All computations were carried out on a commonly used computer and the Generalized Gradient-based method was used as the optimization algorithm. Finally, the managers implemented the optimal values for the decision variables derived from the computation.

3 The mathematical model

The decision variables in this problem are $L_i^e(k)$ and $t_i(k)$. However, three parameters are fuzzy including $Q_i^e(k)$, $\tilde{L}_i(k)$, and $\tilde{k}(k)$. Two values have optimized the problem, which are explained as follows: first, the fuzzy-based-expectation value of the wastewater amount that is processed on each facultative pond. This value was maximized because the wastewater needs to be processed on the facultative pond. Furthermore, this value was calculated for each facultative ponds, as well as the periodic review times that were considered to be optimal, and formulated as follows:

$$\max Z = \tilde{E}\left[\sum_{k=1}^{K}\sum_{i=1}^{4} L_i^e(k)\right]. \tag{1}$$

Second, the difference between the actual efficiency and reference values is considered by managers. This value is minimized in an attempt to bring the actual values close to their reference values. Consequently, it will be formulated as a quadratic function, hence, the entire objective function will be in quadratic form. The whole optimization problem is classified as quadratic optimization models, and the value is formulated as follows:

$$\min Z = \tilde{E}\left[\sum_{k=1}^{K}\sum_{i=1}^{4} \left(E_i(k) - E_i^r(k)\right)^2\right]. \tag{2}$$

Based on the optimization theory (see e.g., [32]), a minimization problem can be converted as a maximization of the minus of the objective function, then the two

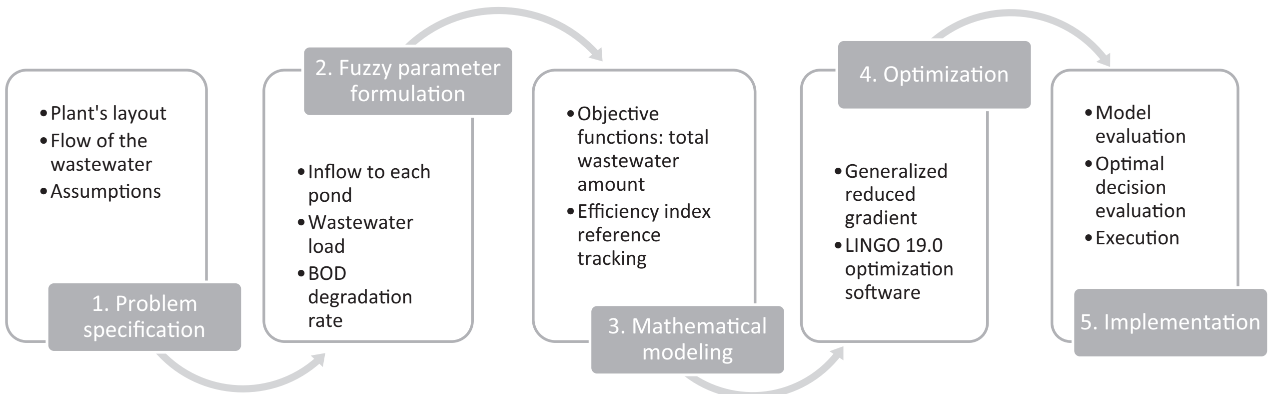

Fig. 2. Problem solving steps.

objective functions above can be combined into a single minimization problem as follows:

$$\max Z = \tilde{E}\left[\sum_{k=1}^{K}\sum_{i=1}^{4}\left(L_i^e(k) - \left(E_i(k) - E_i^r(k)\right)^2\right)\right]. \quad (3)$$

Note that the notation $\tilde{E}[\cdot]$ denotes the expectation value in the fuzzy sense (more details follow). Also, Constraint functions are formulated in the following list:

– Let k be the percentage of the biological oxygen demand degradation rate and t be the duration of the wastewater processing time. The efficiency index value for each facultative pond i is calculated as follows:

$$E_i = \frac{k.t}{1+k.t}, \forall i,$$

$$E_i(k)C_i(k) \leq BM, \forall i = 1,2,3,4; \forall k = 1,2,..,K, \quad (4)$$

– The wastewater load entering the ponds must be less than or equal to the maximum value of the wastewater load prior to the ponds. This is formulated as follow:

$$L_i^e(k) \leq \tilde{L}_i(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K, \quad (5)$$

Since the wastewater load on ponds III and IV is half of those on ponds I and II, the above constraints can be reformulated as follows:

$$L_1^e(k) \leq \tilde{L}_1(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K;$$

$${}^{3e}_{L}(k) \leq \tilde{L}_1(k) - L_1^e(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K;$$

$$L_2^e(k) \leq \tilde{L}_2(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K;$$

$$L_4^e(k) \leq \tilde{L}_2 - L_2^e(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K;$$

–The wastewater load entering each facultative pond is equal to the flow rate. This is written as follows:

$$L_i^e(k) = \frac{\left(\tilde{Q}_i^e(k).C_i(k)\right)}{1000}, i = 1,2,3,4. \quad (6)$$

– Summarizing the mathematical model above, it can be rewritten as follows:

$$\max Z = \tilde{E}\left[\sum_{i=1}^{4}\left(L_i^e(k) - \left(E_i(k) - E_i^r(k)\right)^2\right)\right] \quad (7)$$

subject to:

$$\begin{aligned}
E_i(k)\cdot\frac{\left(1000\cdot\tilde{L}_i(k)\right)^e}{\tilde{Q}}{}_i(k) &\leq BM, \forall i = 1,2,3,4, \forall k \\
&= 1,2,..,K; \\
L_1^e(k) &\leq \tilde{L}_1(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K; \\
L_3^e(k) &\leq \tilde{L}_1(k) - L_1^e(k), \forall i = 1,2,3,4, \forall k \\
&= 1,2,..,K; \\
L_2^e(k) &\leq \tilde{L}_2(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K; \\
L_4^e(k) &\leq \tilde{L}_2 - L_2^e(k), \forall i = 1,2,3,4, \forall k = 1,2,..,K; \\
\left(1+\tilde{k}(k)\cdot t_i(k)\right)E_i(k) &= \tilde{k}(k)\cdot t_i(k), \forall i = 1,2,3,4, \forall k \\
&= 1,2,..,K.
\end{aligned}$$

The model's objective function is in a quadratic form, while the constraint functions are in a linear form except the last one which is nonlinear as it contains multiplication of two unknowns. The optimal solution exists as long as the feasible region does not empty, based on the optimization theory [32]. Furthermore, the model also belongs to nonlinear optimization model with the nonlinearity degree of two as the nonlinearity only appears with the quadratic form in the objective function and in the last constraint function.

The fuzzy variables in the problem were assumed to have discrete membership functions. For a fuzzy variable ξ, the membership function is considered as follows:

$$\mu_\xi(x) = \begin{cases} \mu_1, \text{if} x = x_1 \\ \mu_2, \text{if} \, x = x_2 \\ \vdots \\ \mu_m, \text{if} \, x = x_m \end{cases}, \quad (8)$$

where x_1, x_2, ..., x_m are distinct and $x_m > x_{m-1} > \ldots > x_2 > x_1$. The expectation value of ξ in the fuzzy sense is given by $E[\xi] = \sum_{i=1}^{m} w_i x_i$ where $w_i = \frac{1}{2} \left(\max_{1 \le j \le i} \mu_j - \max_{1 \le j < i} \mu_j + \max_{i \le j \le m} \mu_j - \max_{1 < j \le m} \mu_j \right)$ for $i = 1, 2, \ldots, m$ [33].

4 Numerical experiment results and discussions

4.1 Parameter setup

This study used secondary data, which was obtained from published works in recent years. First, the average wastewater load inflow was 4.799,6 kg/day and the biological oxygen demand degradation coefficient was 1.1% [30]. Meanwhile, data for the membership functions for the fuzzy variables were randomly generated, these are explained as follows:

The reference value for the treatment efficiency index was required to compute the optimal decision, where $E_{1,2}^r = 0.15$and$E_{3,4}^r = 0.25$were used. Moreover, the previous parameter values were inputted in LINGO 19.0 software on a regularly used computer. All calculations were also performed in LINGO 19.0, and the generalized reduced gradient algorithm was utilized to solve the optimization problem (7); for technical details about this optimization algorithm, one may refer to [32].

4.2 Results and discussions

The computations were conducted in a computer within minutes; hence, the computation time was not an issue. Furthermore, the optimization problem (7) was always well-defined/solvable, i.e., an optimal decision always exists with the data provided in the experiment, and the

$$\mu_{Q_i^e(k)}(x) = \begin{cases} 0.10, & \text{if } Q_i^e(k) = 10900 \\ 0.20, & \text{if } Q_i^e(k) = 10950 \\ 0.25, & \text{if } Q_i^e(k) = 11000 \\ 0.50, & \text{if } Q_i^e(k) = 11050 \\ 0.75, & \text{if } Q_i^e(k) = 11100 \\ 0.90, & \text{if } Q_i^e(k) = 11150 \\ 1.00, & \text{if } Q_i^e(k) = 11200 \\ 0.75, & \text{if } Q_i^e(k) = 11250 \\ 0.60, & \text{if } Q_i^e(k) = 11300 \\ 0.50, & \text{if } Q_i^e(k) = 11350 \\ 0.00, & \text{otherwise} \end{cases}$$

$$\mu_{\tilde{L}_{i=1,2}(k)}(x) = \begin{cases} 0.10, & \text{if } \tilde{L}_i(k) = 2390 \\ 0.20, & \text{if } \tilde{L}_i(k) = 2400 \\ 0.25, & \text{if } \tilde{L}_i(k) = 2410 \\ 0.50, & \text{if } \tilde{L}_i(k) = 2420 \\ 0.75, & \text{if } \tilde{L}_i(k) = 2430 \\ 0.90, & \text{if } \tilde{L}_i(k) = 2440 \\ 1.00, & \text{if } \tilde{L}_i(k) = 2450 \\ 0.75, & \text{if } \tilde{L}_i(k) = 2460 \\ 0.60, & \text{if } \tilde{L}_i(k) = 2470 \\ 0.50, & \text{if } \tilde{L}_i(k) = 2480 \\ 0.00, & \text{otherwise} \end{cases}$$

$$\mu_{\tilde{L}_{i=3,4}(k)}(x) = \begin{cases} 0.10, & \text{if } \tilde{L}_i(k) = 1195 \\ 0.20, & \text{if } \tilde{L}_i(k) = 1200 \\ 0.25, & \text{if } \tilde{L}_i(k) = 1205 \\ 0.50, & \text{if } \tilde{L}_i(k) = 1210 \\ 0.75, & \text{if } \tilde{L}_i(k) = 1215 \\ 0.90, & \text{if } \tilde{L}_i(k) = 1220 \\ 1.00, & \text{if } \tilde{L}_i(k) = 1225 \\ 0.75, & \text{if } \tilde{L}_i(k) = 1230 \\ 0.60, & \text{if } \tilde{L}_i(k) = 1235 \\ 0.50, & \text{if } \tilde{L}_i(k) = 1240 \\ 0.00, & \text{otherwise} \end{cases}$$

$$\mu_{\tilde{k}(k)}(x) = \begin{cases} 0.10, & \text{if } \tilde{k}(k) = 1.04 \\ 0.20, & \text{if } \tilde{k}(k) = 1.05 \\ 0.25, & \text{if } \tilde{k}(k) = 1.06 \\ 0.50, & \text{if } \tilde{k}(k) = 1.07 \\ 0.75, & \text{if } \tilde{k}(k) = 1.08 \\ 0.90, & \text{if } \tilde{k}(k) = 1.09 \\ 1.00, & \text{if } \tilde{k}(k) = 1.10 \\ 0.75, & \text{if } \tilde{k}(k) = 1.11 \\ 0.60, & \text{if } \tilde{k}(k) = 1.12 \\ 0.50, & \text{if } \tilde{k}(k) = 1.12 \\ 0.00, & \text{otherwise} \end{cases}$$

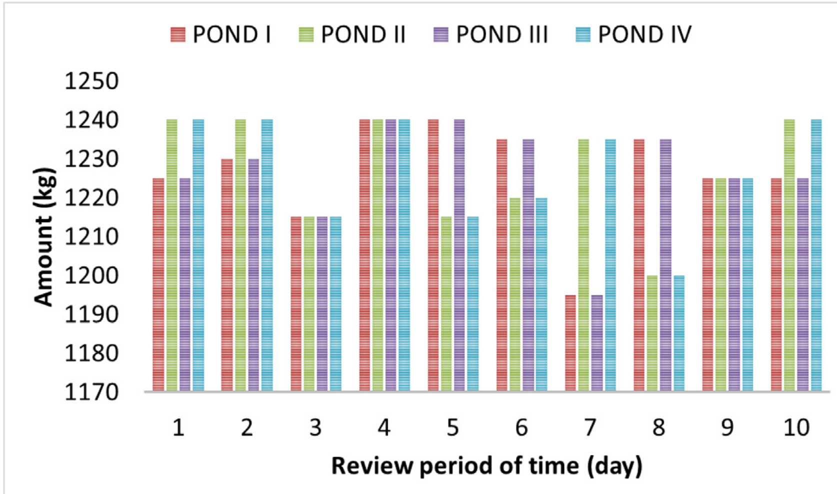

Fig. 3. Wastewater load volume to be processed in each pond.

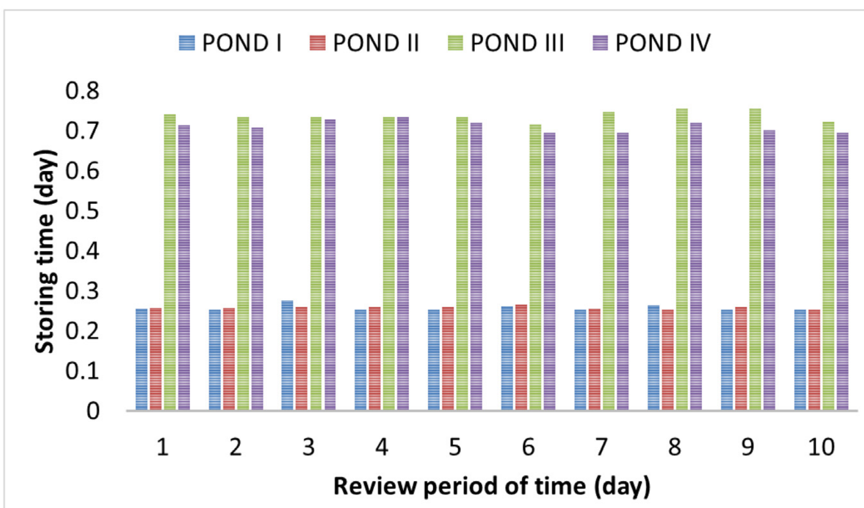

Fig. 4. Storing time duration to process wastewater in each pond.

optimization algorithm was always convergence within minutes. Furthermore, LINGO optimization software was successfully implemented the generalized reduced gradient algorithm and solved the optimization problem (7). Figures 3 and 4 depicted the optimal decisions for wastewater load volume to be processed in the facultative pond i $\left(L_i^e\right)$ and storing time (t_i), respectively. The decisions were derived from the optimization model (7), and recommended based on the optimization solutions.

Figure 3 showed the optimal decisions of the wastewater load volume to be processed in each pond, and these decisions were implemented by the managers. Figure 4 indicated the optimal storing time for each pond. However, the managers can process the wastewater longer than these decisions to produce better water.

Due to lack of existing studies for similar specifications, the results above were compared only with decisions without optimization reported in [7]. These nonoptimized decisions were implemented by the managers based on their intuition without any structural decision-making support. For nonoptimized decisions, the average processed wastewater load was 4,799 kg/day whereas the proposed model provided 4,907 kg/day, which improved the performance by 2.25%. One may argue that this is not significant. However, in terms of the storing/retention time, the proposed model significantly improved the performance of the plant; this is explained as follows: the average storing time without optimization was 4.83 day whereas our proposed optimization model provided 1.96 day. This improved the performance by 59.4%, which is very significant.

In terms of the mathematical model forms, our proposed model can accommodate three fuzzy parameters. This is very useful for situations in which the parameters are uncertain and historical data are not available or do not represent the current real situation; this is the main advantage of the proposed model in this paper. Furthermore, model (7) also can accommodate multi-period of observations. Meaning that the model can be used to determine optimal decisions for multiple periods of wastewater treatments as shown in Figure 4 in which the model was implemented for 10 multiple periods (days).

From the results and the evaluation of the mathematical optimization model proposed in this study, the following managerial insights can be drawn. First, some assumptions can be relaxed by the managers, however, the model should be adjusted. For example, if managers consider the presence of sunlight, the model needs to be modified to switch between wastewater processes with/without sunlight. Second, the managers can modify the membership functions of the fuzzy parameters in the model at any time. Although when they change, new computations need to be conducted to calculate the new optimal decisions. This is not possible, especially when the computational time is limited. Third, when the number of samples, or possible values of fuzzy parameters, is large enough, the computational time will increase. The managers should take this into consideration.

5 Conclusions and future research direction

This study proposed a fuzzy-based optimization model used by the managers of wastewater treatment plants to calculate the optimal amount of wastewater to be pumped in facultative ponds and the storing time. The results showed that the proposed model was successful, and can be used in the maintenance of wastewater treatment plants.

The proposed mathematical model described the dynamics of the wastewater biological oxygen demand only in facultative ponds and processes in maturation ponds were excluded, this was the main limitation of this study. This is because a further mathematical model is required to study the dynamics of the plant parts including maturation ponds and other chemical/biological components to optimize the whole processes in the plant. Therefore, as a future research direction, one can built a new model for the processes in maturation ponds and integrate it with the model for the processes in facultative ponds.

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