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Bi-Objective Optimisation Model for Phosphorous Removal in Wastewater Treatment Plants

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Phosphorous, which is extracted from non-renewable rock reserves found in select countries, is a valuable resource for food production. With the increasing demand for food production, it is projected that the rock reserves will be exhausted within the century. Sustainable alternatives should be explored to satisfy the global demand of future generations. Nitrogen and phosphorous are required nutrients for crop growth. These nutrients can be found in wastewater which can be recovered using nutrient recovery technologies in sewage treatment plants (STPs) and subsequently transformed into valuable fertiliser. This approach can reduce the dependence on costly commercial fertilisers and help STPs comply with stringent effluent standards. A sewage treatment plant requires multiple treatment levels before the wastewater is discharged to receiving water bodies. The performance of a technology to remove nutrients from wastewater depend on several factors like influent characteristics and operating conditions. The challenge is in determining the appropriate series of treatment technologies which maximises P-removal while also reducing total annualised costs (TAC). This study develops a lexicographic ε-constraint optimisation model with TAC and overall phosphorous removal efficiency to address this problem. In comparison to most previous studies, the study also considered that the effluent may be used for irrigation provided that the effluent characteristics satisfy the standards for irrigation. The model was implemented to determine the optimal series of technologies for a 10,000 m^3/d STP with medium-strength influent characteristics and subject to regulatory standards for discharge and reuse applications. Using lexicographic ε-constraint method, the optimal superstructure utilises MBR with an overall phosphorous efficiency of 100 % and cost of USD 49,877,190,000.

1. Introduction

Phosphorous (P) is extracted from phosphate rock reserves found in selected countries (Jasinski, 2021), and is a valuable element for fertiliser production (Daneshgar et al., 2018). The continuous increase in demand for fertiliser brought by the rapid increase in population will likely exhaust the current supply of phosphate rock reserves within the century (Cordell et al., 2009). This will have a huge impact on global food security, especially for developing countries that heavily depend on commercial fertiliser to grow crops.

The nutrients in wastewater are potential N and P source for fertiliser production and can be recovered using biological nutrient removal (BNR) technologies such as anaerobic/anoxic/oxic (A^2O), membrane bioreactor (MBR), University Cape Town (UCT), among others (Tchobanoglous et al., 2013). In BNR technologies, nitrogen is removed via nitrification-denitrification processes, while phosphorous removal is carried out by the polyphosphate-accumulating organisms (PAOs) at anaerobic and aerobic conditions. The phosphorous is removed from the system as excess sludge (Tchobanoglous et al., 2013). Nutrients can also be removed from wastewater using chemical or combined biological-chemical methods. The chemical method requires the addition of metal salts such as iron and aluminium, resulting in the precipitation of iron phosphates and aluminium phosphates (Tchobanoglous et al., 2013).

In planning and designing an STP for nutrient removal, the operating conditions of a technology such as carbon source, detention times, dissolved oxygen concentrations, and internal recycling ratios, among others, should be met to achieve high nutrient removal performance (Tchobanoglous et al., 2013). The STP may have the

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highest P-removal performance using advanced treatment technologies but may not be feasible due to its high investment and operating costs. Alternatively, the proposed STP may have the lowest cost at the expense of low P-removal performance. It is necessary to determine the appropriate series of treatment technologies that could provide the highest P-removal at an acceptable cost while meeting the stringent effluent requirements.

The use of mathematical programming will be useful in determining the optimal superstructure. In dealing with multiple and potentially conflicting objectives of the system, multi-objective optimisation (MOO) methods such as simple additive weighting (SAW) and ε-constraint can be used. These approaches generate non-dominated solutions called Pareto-optimal solutions. Bozkurt et al. (2015) proposed a superstructure framework for the full-scale retrofitting design of a wastewater treatment plant. Castillo et al. (2016) proposed an initial screening of the superstructure using decision support tools before performing multi-objective optimisation. Padrón-Páez et al. (2020) performed lexicographic ε-constraint optimisation with three objective functions, followed by multi-criteria decision analysis (MCDA) for the selection of the optimal network. Ho et al. (2021) utilised fuzzy optimisation to determine the most sustainable wastewater treatment plant for the sago manufacturing industry, considering the investment cost, area footprint, and carbon footprint as objective functions. Few studies only explored bi-objective optimisation with total costs and overall phosphorous removal efficiency as the objectives. Most studies focused on the compliance of the wastewater treatment plant with the effluent standards. Padrón-Páez et al. (2020) included wastewater reuse as sink alternative.

This work aims to develop a bi-objective optimisation model which minimises total costs and maximises phosphorous removal as the two conflicting objective functions. The model utilised the lexicographic ε-constraint method, an optimisation method proposed by Mavrotas (2009), which generates efficient and non-dominating solutions. Section 2 defines the problem statement, variables and parameters of the study while Section 3 discusses the equations for the development of the model. The proposed model is then simulated using a case study for an STP treating medium-strength wastewater subject to requirements for discharge and irrigation. The study considered BNR technologies only since the phosphorous removed from these technologies can be recovered and converted into a slow-release fertiliser called struvite. The life cycle assessment by Pausta et al. (2018) showed that the combined BNR technologies and nutrient recovery technologies can significantly reduce the eutrophication and global warming impacts of STPs and satisfy, the stringent effluent requirements implemented by the regulatory authorities. Although chemical precipitation can achieve high P removal, the low dissolution of phosphorous from metal phosphates makes it an unsuitable option for P recovery to be used as a fertiliser (Perera et al., 2019).

2. Problem statement

The study aims to develop a bi-objective optimisation problem which minimises the total annualised cost (TAC) and maximises the overall phosphorous removal (η_{TP}) from the STP. The formal problem statement is given as follows: Wastewater with known influent concentration for contaminant i (c_i^{in}) enters the STP at a given constant flowrate Q. The STP consists of T number of treatment levels represented by index t and N number of technology alternatives per treatment level represented by index n_t. Each technology n in each treatment level t has a corresponding known removal efficiency $\eta_{t,n,i}$ for contaminant i. At the end of the final treatment, there are O number of sinks (represented by index s) each having a maximum allowable concentration $c_{s,i}$ for each contaminant i. The objective is to determine the right combination of technologies which will maximise P-removal or minimise total annual cost. The superstructure of the problem is illustrated in Figure 1 below.

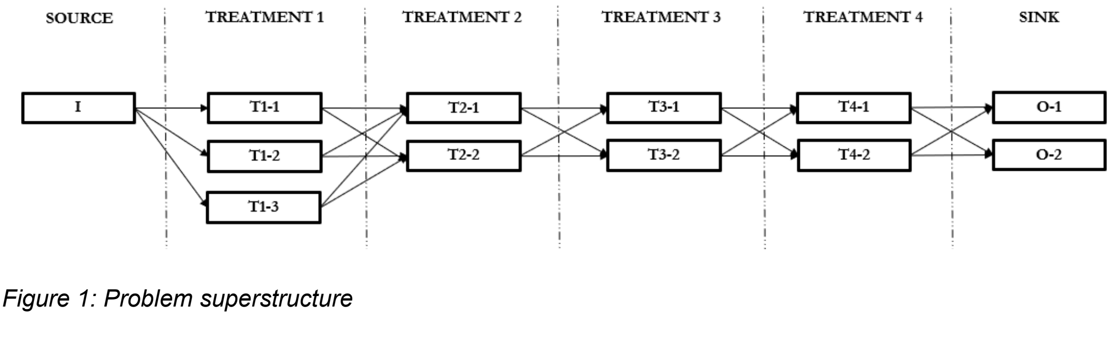

Figure 1: Problem superstructure

3. Model formulation

The total annualised cost (TAC) of a sewage treatment plant is defined as the sum of the annualised capital costs (ACC) and annual operating costs (AOC) as shown in Eq(1). Aside from the TAC, the overall total phosphorous (TP) removal efficiency (η_{TP}) of the STP is considered. η_{TP} is calculated by determining the overall

TP removed over the influent TP (F_{TP}^{in}) in kg as shown in Eq(2). The influent TP ($C_{i=TP}^{in}$) and $Q_{t,n}$ are initially given in the problem while the final TP concentration ($C_{t,n,i=TP}$) is only known after the model is able to determine the appropriate series of treatment technologies. $Q_{t,n}$ remains constant throughout the STP.

$$TAC = annual\ capital\ cost\ (ACC) + annual\ operating\ cost(AOC) \tag{1}$$

$$\eta_{TP} = 100 * \left[\frac{F_{t=1,n,i=TP}^{in} - F_{t,n,i=TP}^{out}}{F_{t=1,n,i=TP}^{in}}\right] = 100 * \left[\frac{Q_{t=1,n} * C_{i=TP}^{in} - Q_{t,,n} * C_{t,n,i=TP}}{Q_{t=1,n} * C_{i=TP}^{in}}\right] \tag{2}$$

The volumetric flowrates entering ($Q_{t-1,n}$) and leaving ($Q_{t,n}$) technology alternative n at any treatment level t remains constant as shown in Eq(3). The mass of contaminants at any technology alternative n and treatment level t ($F_{t,n,i}$) can be calculated using Eq(4), and are expressed in kg/d. Eq(5) states that the mass of the contaminant i entering technology alternative n from treatment level t -1 ($F_{t-1,n,i}$) is equal to the mass leaving ($F_{t,n,i}$) and mass removed ($F_{t,n,i}^{waste}$) by technology alternative n at treatment level t. Eq(6) explains that the outlet mass flowrate can be calculated given the efficiency $\eta_{t,n,i}$ and inlet mass flowrate $F_{t,n,i}$. In order to calculate the $F_{t,n,i}$ values at each treatment level t, $F_{t=1,n,i}$ should be given in the problem. The equations for calculating the annual capital and operating costs are expressed in Eq(7) - Eq(8) where FCC and FOC are the fixed costs, VCC and VOC are variable costs multiplied to $Q_{t,n}$, $B_{t,n}$is a binary variable, and AF is the annualising factor (Eq(9)). The capital and operating costs of the technologies vary due to several factors such as the land area occupied, energy requirement, chemical requirement, and labour, among others. AF requires the annual interest α and payback period x in y (Towler and Sinnott, 2008). Eq(10) and Eq(11) represent the flow and volume going to alternative n at treatment level t and indicates that the binary variable $B_{t,n} = 1$ if the flow exists and $B_{t,n} = 0$ if there is none, where K is an arbitrary large number. Eq(12) represents that only one technology n can be implemented at each treatment level t. Eq(13), declares $B_{t,n}$ as a binary variable.

$$\sum_{n}^{n=N} Q_{t-1,n} = \sum_{n}^{n=N} Q_{t,n} \tag{3}$$

$$Q_{t,n} c_{t,n,i} = F_{t,n,i} \tag{4}$$

$$\sum_{n}^{n=N} F_{t-1,n,i} = \sum_{n}^{n=N} F_{t,n,i} + \sum_{n}^{n=N} F_{t,n,i}^{waste} \tag{5}$$

$$\eta_{\mathrm{t,n,i}} = 100 * \left[\frac{F_{t-1,n,i} - F_{t,n,i}}{F_{t-1,n,i}}\right] = 100 * \left[\frac{c_{t-1,n,i} - c_{t,n,i}}{c_{t-1,n,i}}\right] \tag{6}$$

$$ACC = AF \sum_{t}^{t=M} \sum_{n}^{n=N} \left(FCC_{t,n} B_{t,n} + VCC_{t,n} Q_{t,n}\right) \tag{7}$$

$$AOC = \sum_{t}^{T} \sum_{n}^{n=N} \left(FOC_{t,n} B_{t,n} + VOC_{t,n} Q_{t,n}\right) \tag{8}$$

$$AF = \left[\frac{\alpha(1+\alpha)^x}{(1+\alpha)^x - 1}\right] \tag{9}$$

$$F_{t,n} \le KB_{t,n} \tag{10}$$

$$Q_{t,n} \le KB_{t,n} \tag{11}$$

$$\sum_{s}^{O} B_{t,n} = 1 \tag{12}$$

$$B_{t,n} \in \{0,1\} \tag{13}$$

At the tertiary treatment level (t = 4), there are no changes with the concentration of the contaminants entering and leaving the technology alternative n. Wastewater at the final treatment level typically undergoes disinfection prior to discharge or reuse. Eq(14) denotes that the total mass at the tertiary level ($F_{4,n}$) is equal to the total mass (F_s) of the sinks. Eq(15) states that effluent mass flowrate of contaminant i from technology n ($F_{t=4,n,i}^{eff}$) shall satisfy the allowable sink limits ($F_{s,i}^{max}$) in kg/d for discharge and/or reuse. Similar to Eq(10) – Eq(13), a binary variable is introduced to indicate the selection or non-selection of a sink. Eq(17) requires the model to select at least one (1) sink s if it satisfies Eq(16). The binary variable B_s is activated ($B_s = 1$) if the sink is implemented, otherwise, B_s = 0.

$$\sum_{t=4} F_{t,n} = \sum_s^O Q_s\, c_{s,i} = \sum_s^O \mathrm{F}_s \quad (14)$$

$$0 \leq F^{eff}_{t=4,n,i} \leq F^{max}_{s,i} \quad (15)$$

$$F_s \leq KB_s \quad (16)$$

$$\sum_s^O B_s \geq 1 \quad (17)$$

$$B_s \in \{0,1\} \quad (18)$$

Lexicographic ε-constraint method is performed with minimising TAC as the objective function while η_{TP} is considered as constraint. Eq(1) – Eq(2) are expressed as follows:

$$\text{Minimise } TAC = ACC + AOC \quad (19)$$

$$\text{Subject to } \eta_{TP} \geq \varepsilon_2 \quad (20)$$

The mixed-integer non-linear programming (MINLP) model can attain global optimal solutions. In this work, the model was simulated using the software LINGO 19.0 version (Lindo Systems Inc., 2022). The case study was solved with negligible CPU time using an Intel®Core i5-1135G7 CPU @ 2.4 GHz processor and 16 GB RAM.

4. Case study

An STP with a capacity of 10,000 m^3/d is operated to treat a medium-strength wastewater and designed to meet the effluent and/or irrigation standards for biochemical oxygen demand (BOD), total suspended solids (TSS), total nitrogen (TN), and total phosphorous (TP) as shown in Table 1. The STP consists of four (4) treatment levels, namely, preliminary, primary, secondary, and tertiary treatment levels. The preliminary treatment level removes coarse to fine solids and the alternatives are bar screen (BS), coarse screen (CS), and grit chamber (GC). Next, the primary treatment level performs partial removal of contaminants to reduce the load to be treated in the secondary treatment level. Two primary clarifiers (PC1 and PC2) with different efficiencies and costs are considered. The secondary treatment level performs the total degradation of the contaminants, and the alternatives are the anaerobic/anoxic/oxic (A^2O) reactor and membrane bioreactor (MBR). Lastly, the tertiary level performs further treatment of the wastewater prior to disposal. Chlorination (Cl) and by-pass (BP) are the alternatives considered in this treatment level. The effluent from the tertiary level is either discharged to water bodies or used for irrigation, with irrigation requiring a flowrate of $Q_{irrigation}$ > 10 m^3/d. Table 2 provides the removal efficiencies and the cost functions expressed for capital and operating costs of the technologies. AF is calculated using an interest rate (α) of 4 % and x = 30 y (Castillo et al., 2016). The equations for the costs were expressed into linear cost functions for faster simulation in the LINGO 19.0 software.

Table 1: Influent and target effluent wastewater characteristics

Parameter	Unit	Influent c_i^{in} [a]	Sink $c_{s,i}$	
			Effluent	Irrigation
BOD	mg/L	200	50[b]	150
TSS	mg/L	195	100[b]	140
TN	mg/L	35	18[c]	30
TP	mg/L	5.6	4[c]	30

Source: [a]Tchobanoglous et al. (2013); [b]DENR (2016); [c]DENR (2021); [d]DA (2019)

Single objective optimisation is first performed to determine the value ranges for the total cost and phosphorous removal as shown in Table 3. The results show the conflicting nature of the two objectives since minimising the TAC (USD 10,330,050,000) achieved a lower η_{TP} (90.9 %) while achieving a complete TP removal (100 %) resulted in higher total costs (USD 50,327,610,000). The value ranges for the η_{TP} obtained from the single objective optimisation were divided into 7 increments, and the values were used as ε_2 constraints for the lexicographic ε-constraint method. With lexicographic ε-constraint method, the cost obtained at ε > 90.9 % is USD 10,330,050,000 which is similar to the value obtained during the single objective optimisation (minimise TAC only). The A^2O was selected as the optimal technology in the secondary treatment level. At ε > 92.2 – 93.5 %, the model determined that the optimal η_{TP} is 94 % which costs USD 11,141,380,000. Beyond At ε >

94.8 %, the TAC became USD 49,877,190,000 with MBR as the selected technology at the secondary treatment level. Figure 2 shows the TAC vs. the TP removal efficiency and Table 4 for the optimal network
s and effluent concentrations. Aside from the technology in the secondary treatment level, the alternative selected at the tertiary treatment level shifted from chlorination (single objective) to bypass when lexicographic ε-optimisation is performed since the model considers both costs and highest attainable TP removal efficiency. The flowrate for irrigation ($Q_{irrigation}$) is set at > 10 m^3/d, while no constraint is set for discharge ($Q_{discharge}$). The volume of the effluent allocated for irrigation ranged from 1,255 – 9,932 m^3/day. Aside from this, the effluent concentrations in all scenarios (see Table 4) satisfy the requirements for both discharge and irrigation. In theory, STPs employing BNR technologies can satisfy the Philippine standards for discharge and irrigation.

Table 2: Removal efficiencies and cost functions

Level (t)	Technology (n)	% Removal efficiency ($\eta_{t,n,i}$)				ACC (1,000 USD/y)		AOC (1,000 USD/y)	
		BOD	TSS	TN	TP	Fixed ($FCC_{t,n}$)	Variable ($VCC_{t,n}$)	Fixed ($FOC_{t,n}$)	Variable ($VOC_{t,n}$)
1	BS	2.5[a]	5[a]	-	-	7.786[a]	0.002[a]	13.103[a]	0.003[a]
1	CS	6[a]	15[a]	-	-	12.433[a]	0.003[a]	21.343[a]	0.005[a]
1	GC	5[a]	3[a]	-	-	11.529[a]	0.002[a]	19.259[a]	0.004[a]
2	PC1	40[b]	65[b]	40[b]	20[b]	36.861[b]	0.021[b]	-0.493[b]	0.012[b]
2	PC2	30[a]	60[a]	9[a]	9[a]	2.132[a]	0.001[a]	10.437[a]	0.003[a]
3	A^2O	95[b]	95[b]	90[b]	95[b]	71.850[b]	0.012[b]	78.651[b]	0.024[b]
3	MBR	99.1[c]	99.8[c]	87.5[c]	100[c]	59.061[a]	0.043[a]	99.730[a]	0.054[a]
4	Cl	-	-	-	-	17.063[a]	0.007[a]	30.333[a]	0.009[a]

Obtained from [a]Oertlé (2018), [b]Padrón-Páez et al. (2020), and [c]Sadr and Saroj (2015).

Table 3: Results from single objective and lexicographic ε-constraint optimisation

Objective Function	TAC (in 1,000 USD)	η_{TP} (%)	TAC (in 1,000 USD)	η_{TP} (%)
	Single objective		Lexicographic ε-constraint	
Minimise TAC (in 1,000 USD)	103,300.50	90.9	103,300.50	90.9
Maximise η_{TP} (%)	503,276.10	100	498,771.90	100

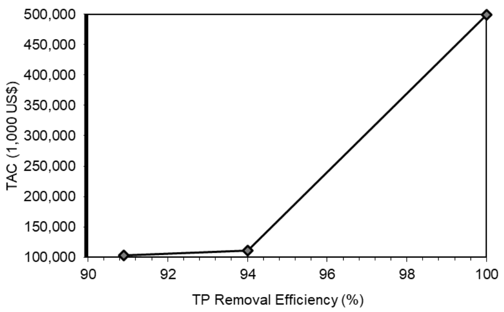

Figure 2: The total annualised cost vs. TP removal efficiency using lexicographic ε-constraint optimisation

Table 4: Optimal treatment networks from single objective and a lexicographic ε-constraint optimisation

Treatment Network	Network	Effluent Concentration (c^{eff}), mg/L			
		BOD_5	TSS	TN	TP
Single objective (Minimise TAC)	BS – PC2 – A^2O – BP	6.83	3.71	1.59	0.51
Single objective (Maximise η_{TP})	GC – PC2 – MBR - BP	1.20	0.15	3.98	0.00
Lexicographic ε-constraint (ε > 92.2 – 93.5 %)	BS – PC1 – A^2O – BP	5.85	3.24	1.40	0.34
Lexicographic ε-constraint (ε > 94.8 %)	BS – PC2 – MBR - BP	1.23	0.19	5.00	0.00

5. Conclusions

The aim of the study is to develop a bi-objective optimisation model that can determine the optimal total annualised costs and overall phosphorous removal efficiency for a sewage treatment plant at any capacity. Literature review showed most studies focused on the compliance of the wastewater treatment plant with the effluent standards. A case study was used to present the capability of the model in determine the appropriate series of treatment technologies to treat medium-strength wastewater entering a 10,000 m^3/d STP and in ensuring that the effluent complied with the effluent standards for discharge and irrigation. The cost functions used in the study was ensured to be applicable at 10,000 m^3/d STP. The proposed model showed the conflicting nature of the objectives in which higher removal efficiency entails higher costs and vice versa. Using lexicographic ε-constraint method, the Pareto-optimal solution selected bar screen (BS), primary clarifier (PC2), membrane bioreactor (MBR) and bypass (BP) costing USD 49,877,190,000 with an overall phosphorous removal efficiency of 100 %. In theory, the effluent produced from the optimal treatment network may be reused for other purposes aside from irrigation due to its low contaminant concentrations. Future work will incorporate more technology alternatives in the superstructure network, integrate sludge treatment technologies capable of nutrient recovery, and develop models which can handle epistemic uncertainties of emerging technologies.

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