

Scheduling of Batch Operation for a Wastewater Treatment Plant under Time-of-Use Electricity Pricing

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Cite This: *ACS Omega* 2022, 7, 28525–28533



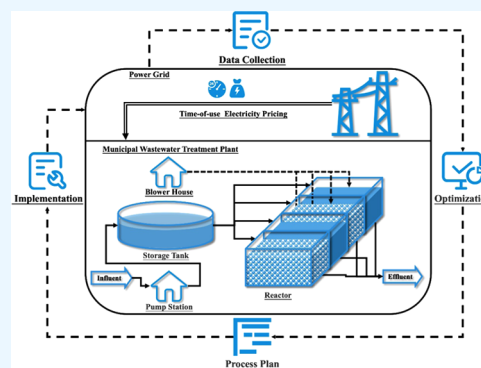
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ABSTRACT: High operating cost caused by electric energy consumption is a common problem challenging many municipal wastewater treatment plants (WWTPs). Due to the characteristics of intermittent inflow and aeration, WWTPs using sequencing batch reactor technology and its variants can be managed to relieve operating cost through taking advantage of time-of-use electricity pricing. However, little attention has been paid to the scheduling of treatment processes in the context of WWTPs. In this paper, a novel mixed-integer linear programming model is established for scheduling the batch operation of a WWTP under time-of-use electricity pricing, which considers constraints arising from task allocation, processing sequence, and processing duration. The modeling method is developed from the event-based continuous-time approach. The start time and end time of each treatment task are optimized to shift electricity consumption from peak hours to off-peak hours to the greatest extent, thus minimizing electricity cost. A case study demonstrates that the proposed model can quickly generate precise operational plans for the investigated WWTP. By implementing the optimum schedules, the WWTP can save on its electricity bill without changing the treatment capacity or the treatment process. The widening of peak and off-peak electricity pricing gap is favorable for the proposed model to display a more significant effect in reducing electricity cost.



1. INTRODUCTION

Wastewater treatment is vital to public health and ecological safety. Take China as an example, the regulatory standards for effluent discharged from municipal wastewater treatment plants (WWTPs) have become more stringent since the State Council issued the Water Pollution Prevention and Control Action Plan in 2015. As terminal treatment facilities, WWTPs usually receive a huge amount of domestic sewage on a daily basis and thus consume enormous amounts of energy to clean it up. As of the end of 2018, a total of 5370 WWTPs have been put into operation in China, with a daily wastewater treatment capacity of about 168 million m³ and an annual power consumption of over 19 billion kW·h.¹ The main power consumption equipment includes air blowers, agitators, pumps, and sludge dewatering machines.² Most municipal wastewater treatments include aerobic processes, and aeration often accounts for more than 50% of the electricity consumed by a WWTP.³ High electricity bills often bring heavy economic burden to WWTPs and even put some of them in difficulties. Currently, lowering electricity cost is a major concern of the wastewater treatment industry.

Sequencing batch reactor (SBR) is a fill-and-draw activated sludge system for both municipal and industrial wastewater treatment. A few variants of SBR have emerged over the past decades, including cyclic activated sludge technology (CAST), intermittent cycle extended aeration system (ICEAS), and

modified sequencing batch reactor (MSBR).⁴ The treatment process in an SBR is characterized by intermittent flow conditions, and the use of high-energy-consuming equipment is concentrated in the stages during which aeration takes place.⁵ Given that time-of-use (TOU) electricity pricing has been widely implemented nowadays,⁶ exploring scheduling of batch operation under TOU electricity pricing provides a possibility to reduce electricity bills for WWTPs using SBR and its variants.

In process industries, scheduling refers to the decision-making process in which shared resources, such as equipment, utilities, and manpower, are allocated to execute tasks over a given time horizon of interest.⁷ Scheduling seeks to maximize productivity, minimize operating costs, achieve efficient inventory management, and/or improve customer satisfaction, which plays an important role in most manufacturing and service industries. To solve scheduling problems, mathematical programming has long been a popular approach, for it can

Received: May 27, 2022

Accepted: July 27, 2022

Published: August 8, 2022



provide scheduling schemes despite the complex nature of real problems.^{8,9} Based on time representation, a critical aspect of scheduling models, mathematical programming approaches can be mainly classified into discrete-time and continuous-time.¹⁰ The discrete-time modeling approach divides the time horizon into a number of time intervals of specified length, in which the start and end time of an event assigned to an interval must be exactly at the time interval points.¹¹ The discrete-time approach is conceptually straightforward and can be easily extended to address various processing features.¹² It is often necessary to define very small time grid to improve the accuracy of a discrete-time model. However, this will increase the number of time intervals and the size of the model, resulting in low computational efficiency or even infeasible solution.¹³ The continuous-time modeling approach divides the time horizon into intervals of unknown length by the time points at which an event starts and ends. This approach can be further classified into slot-based,¹⁴ global event-based,¹⁵ unit-specific event-based,¹⁶ and sequence-based¹⁷ modeling methods. Compared with discrete-time models, continuous-time models are usually of smaller sizes and require less computational efforts for solution, but their structures tend to be more complicated, which makes formulating models tougher.⁸

Scheduling models have been developed for industries such as petrochemical industry,¹⁶ mining,¹⁸ metallurgy,¹⁹ food processing,²⁰ agricultural irrigation,²¹ and scientific testing services.²² Water is often the target to be dispatched in industrial scheduling problems. Many researchers have studied the synthesis and optimization of batch water networks. For example, Pulluru and Akkerman²³ proposed a scheduling approach to capture the main characteristics of water flows in batch process plants. Zhang et al.²⁴ and Deng et al.²⁵ modeled membrane-based desalination systems to maximize water production ratio while minimizing storage tank capacity. The operation duration and time schedule for semicontinuous units were considered in their models. However, studies on scheduling of intermittent wastewater treatment processes are rare in the literature, and fewer have involved TOU pricing. Simon-Várhelyi et al.²⁶ proposed a storage scheduling strategy for the WWTP to reduce electricity cost, but they did not clarify how the starting storage and subsequent treatment time moments of each investigated case were determined. Their strategy seems unable to cope with multiple TOU periods appearing in one day since it considers only daytime and nighttime. In addition, storing influent wastewater for 10 h or even longer might be infeasible for WWTPs with small land occupation and limited storage capacity. Moazeni and Khazaei²⁷ proposed an economic dispatch model to perform co-optimization of WWTPs interconnected with smart grids, but they focused on allocating energy generation resources rather than scheduling batch processes, and they did not consider the TOU electricity pricing of external grids. In practical engineering, heuristic-based or spreadsheet-based scheduling methods are still commonly used for managing WWTPs. These methods are limited to generate schedules for simple processes and often lead to suboptimal results.¹¹ Mathematical programming has yet to be well utilized in optimizing the operations of WWTPs.

In this paper, the feasibility of reducing electricity cost for WWTPs through managing the treatment processes under TOU electricity pricing is explored. Based on the continuous-time modeling approach, a new mixed-integer linear programming (MILP) model is proposed to generate the

optimal schedule of batch operation for a WWTP. The performance of the proposed model is demonstrated by solving the scheduling problem of a real-world WWTP. The effects of applying the proposed model under varying TOU pricing scenarios are also discussed.

2. PROBLEM DESCRIPTION

WWTPs considered in this study use SBR or variants of SBR as the core biological wastewater treatment technology. The SBR process usually has five stages, fill, react, settle, decant, and idle. These stages take place sequentially in one reactor, and they are controlled by time to achieve the effluent quality and treatment capacity.²⁸ In the “fill” stage, the influent is pumped into the partially filled reactor until the preset water depth is reached. The “react” stage begins with turning on the aerators, and aerobic biochemical reactions occur in this stage. Once all of the aerators and agitators are turned off, the reactor enters the “settle” stage automatically, in which biomass settles, and meanwhile anoxic reactions may still proceed. In the “decant” stage, the treated supernatant is discharged by lowering decanters down below the water surface. The decanters will be lifted to the rest position when the minimum water level is reached. The “idle” stage is regarded as the period between the end of decanting and the start of the next water inflow.

Normally, real-world WWTPs using SBR have multiple tank reactors so that the influent and effluent can be almost continuous from the perspective of the whole plant, if each individual reactor is properly scheduled. In this study, the plant can be described as a multistage facility that processes a set of production tasks with multiple units. Treated water is the only type of product considered. Biological tank reactors are regarded as units that undertake production tasks. Each production task must be processed in exactly one unit. Each unit processes only one task at a time. All of the products follow the same sequence of stages in processing, and no stage can be skipped.

To simplify the problem, the main assumptions are as follows: (1) No resource constraints except equipment are considered. (2) Since there is no need for unit cleaning or preparing, and the start-up and shutdown of equipment are fast, the switchover times are ignored. (3) The inflow rate and outflow rate of the reactor are assumed to be constant, and the treatment capacity of each batch is assumed to be a fixed number. (4) The processing duration times are prespecified based on expertise and engineering experiences, which ensures the water quality of the effluent meets discharging standards.

The scheduling problem in the context of WWTPs is to determine the optimal start and end time of each stage in each treatment batch within each unit. Taking TOU electricity pricing into account, the scheduling horizon is divided into several time periods. Assigning the same processing stage to different TOU periods may result in different electricity cost; therefore, the ultimate goal of this scheduling problem is minimizing the total electricity cost for WWTPs.

3. MATHEMATICAL FORMULATION

A novel MILP model is proposed to address the scheduling problem for the batch operation of a WWTP. The model is developed using the continuous-time modeling approach, specifically the unit-specific event-based modeling approach. The timing variables are referred to as event points, which are defined based on the processing stages in batch tasks. Each

unit has independent event points, which means event points for different units can start or end at different times. The unit-specific event-based modeling approach divides the scheduling horizon by event points.

The proposed model is presented by (1) introducing the basic sets and indices; (2) categorizing the constraints according to the type of decisions they subject to; and (3) giving the objective function.

3.1. Sets and Indices. In general, a WWTP using SBR or SBR-derived technology includes I ($I = 1, 2, 3, \dots, I$) parallel biological reactors and J ($j = 1, 2, 3, \dots, J$) machines such as sewage pumps, sludge pumps, blowers, mixers, valves, and decanters. A batch task includes L ($l = \text{fill, react, settle, decant}$) stages. A reactor needs to undertake M ($m = 1, 2, 3, \dots, M$) cycles of batch tasks within the scheduling horizon. The scheduling horizon is divided into Y ($y = 1, 2, 3, \dots, Y$) time periods with different TOU electricity prices.

3.2. Constraints. **3.2.1. Allocation Constraints.** Equations 1 and 2 together allocate the start time of an event to a certain time period. T_{ys} and T_{yf} represent the start and end times of time period y , respectively. $T_{s_{i,l,m,y}}$ is the decision variable indicating the start time of stage l in cycle m of reactor i during time period y . Binary variable $XT_{s_{i,l,m,y}}$ is defined to denote whether $T_{s_{i,l,m,y}}$ is located in time period y . If yes, $XT_{s_{i,l,m,y}} = 1$; otherwise, $XT_{s_{i,l,m,y}} = 0$. Equation 1 determines which time period $T_{s_{i,l,m,y}}$ belongs to. Equation 2 ensures that $T_{s_{i,l,m,y}}$ can be assigned to only one time period within the scheduling horizon. In eq 3, $OT_{s_{i,l,m}}$ is the variable representing the optimal start time of an event, and it is obtained by adding up all of the decision variables $T_{s_{i,l,m,y}}$.

$$(XT_{s_{i,l,m,y}})T_{ys} \leq T_{s_{i,l,m,y}} \leq (XT_{s_{i,l,m,y}})T_{yf} \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (1)$$

$$\sum_y XT_{s_{i,l,m,y}} = 1 \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (2)$$

$$\sum_y T_{s_{i,l,m,y}} = OT_{s_{i,l,m}} \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (3)$$

Similarly, in eq 4, the decision variable $T_{f_{i,l,m,y}}$ is defined to express the end time of stage l in cycle m of reactor i during time period y , and binary variable $XT_{f_{i,l,m,y}}$ is defined to denote whether $T_{f_{i,l,m,y}}$ is located in time period y . If yes, $XT_{f_{i,l,m,y}} = 1$; otherwise, $XT_{f_{i,l,m,y}} = 0$. Equations 4 and 5 together allocate $T_{f_{i,l,m,y}}$ to only one time period within the scheduling horizon. Equation 6 determines the optimal end time of an event, $OT_{f_{i,l,m}}$ by adding up $T_{f_{i,l,m,y}}$ of all time periods.

$$(XT_{f_{i,l,m,y}})T_{ys} \leq T_{f_{i,l,m,y}} \leq (XT_{f_{i,l,m,y}})T_{yf} \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (4)$$

$$\sum_y XT_{f_{i,l,m,y}} = 1 \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (5)$$

$$\sum_y T_{f_{i,l,m,y}} = OT_{f_{i,l,m}} \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (6)$$

3.2.2. Sequencing Constraints. In every batch treatment, the processing stages are carried out in sequence in a reactor. Hence, a few sequencing constraints must be obeyed. Equation

7 expresses that a reactor is allowed to be idle after the completion of wastewater feed. Turning on blowers for aeration marks the beginning of a react stage. When the start time of the react stage in cycle m of reactor i ($OT_{s_{i,\text{React},m}}$) equals the end time of the fill stage in the same cycle of the same reactor ($OT_{f_{i,\text{Fill},m}}$), aeration begins immediately after wastewater feed completes. When $OT_{s_{i,\text{React},m}}$ is larger than $OT_{f_{i,\text{Fill},m}}$ the influent wastewater is temporally stored in the reactor, waiting for aeration to start later.

$$OT_{f_{i,\text{Fill},m}} \leq OT_{s_{i,\text{React},m}} \quad \forall i \in I, m \in M \quad (7)$$

Equation 8 indicates the relationship between the end time of the react stage in cycle m of reactor i ($OT_{f_{i,\text{React},m}}$) and the start time of the settle stage in cycle m of reactor i ($OT_{s_{i,\text{Settle},m}}$). The end of react stage is defined by the shutdown of blowers and agitators, after which settling of particles will occur immediately. Therefore, there is no interval between the time point at which the reaction ends and the time point at which settling begins. It is worth noting that the so-called react stage refers to the stage in which aerobic reactions mainly take place. Some anoxic reactions can occur in the following stage.

$$OT_{f_{i,\text{React},m}} = OT_{s_{i,\text{Settle},m}} \quad \forall i \in I, m \in M \quad (8)$$

Equation 9 expresses that the end time of settle stage in cycle m of reactor i ($OT_{f_{i,\text{Settle},m}}$) is the same as the start time of the decant stage in cycle m of reactor i ($OT_{s_{i,\text{Decant},m}}$). To align with how each stage is defined in on-site management, the settle stage is considered to be completed once the decant stage begins, although particles settling and anoxic biodegradation may still proceed in the reactor.

$$OT_{f_{i,\text{Settle},m}} = OT_{s_{i,\text{Decant},m}} \quad \forall i \in I, m \in M \quad (9)$$

Equation 10 indicates that the decant stage of the current cycle must be completed before the fill stage of the next cycle kicks off. The end time of the decant stage in cycle m of reactor i is denoted as $OT_{f_{i,\text{Decant},m}}$ and the start time of the fill stage in cycle $m+1$ of reactor i is denoted as $OT_{s_{i,\text{Fill},m+1}}$. There is no pause between the two cycles if $OT_{s_{i,\text{Fill},m+1}}$ equals $OT_{f_{i,\text{Decant},m}}$. The reactor is left idle between two cycles if $OT_{s_{i,\text{Fill},m+1}}$ is greater than $OT_{f_{i,\text{Decant},m}}$.

$$OT_{f_{i,\text{Decant},m}} \leq OT_{s_{i,\text{Fill},m+1}} \quad \forall i \in I, m \in M \quad (10)$$

Besides the sequencing constraints caused by the characteristics of SBR, resource limitations might impose sequence constraints on certain operations of the plant, in particular, inflow, aeration, and outflow. Some parallel units cannot undergo the same processing stage simultaneously if they share a facility that can only serve one unit or a fixed number of units at a time. For instance, assuming multiple reactors share the same influent pump, these reactors may not be able to get wastewater feed at the same time due to restrictions on flow rate. Similarly, multiple reactors sharing the same blower may have to conduct aeration one by one. If necessary, the additional sequencing constraints can be introduced to regulate the order in which different reactors are engaged in the same processing stage that are given by eqs 11 and 12.

$$OT_{f_{i,l,m}} \leq OT_{s_{i,l',m}} \quad \forall (i, i') \in I, i < i', m \in M \\ l \in \{\text{“fill”}, \text{“react”}, \text{“decant”}\} \quad (11)$$

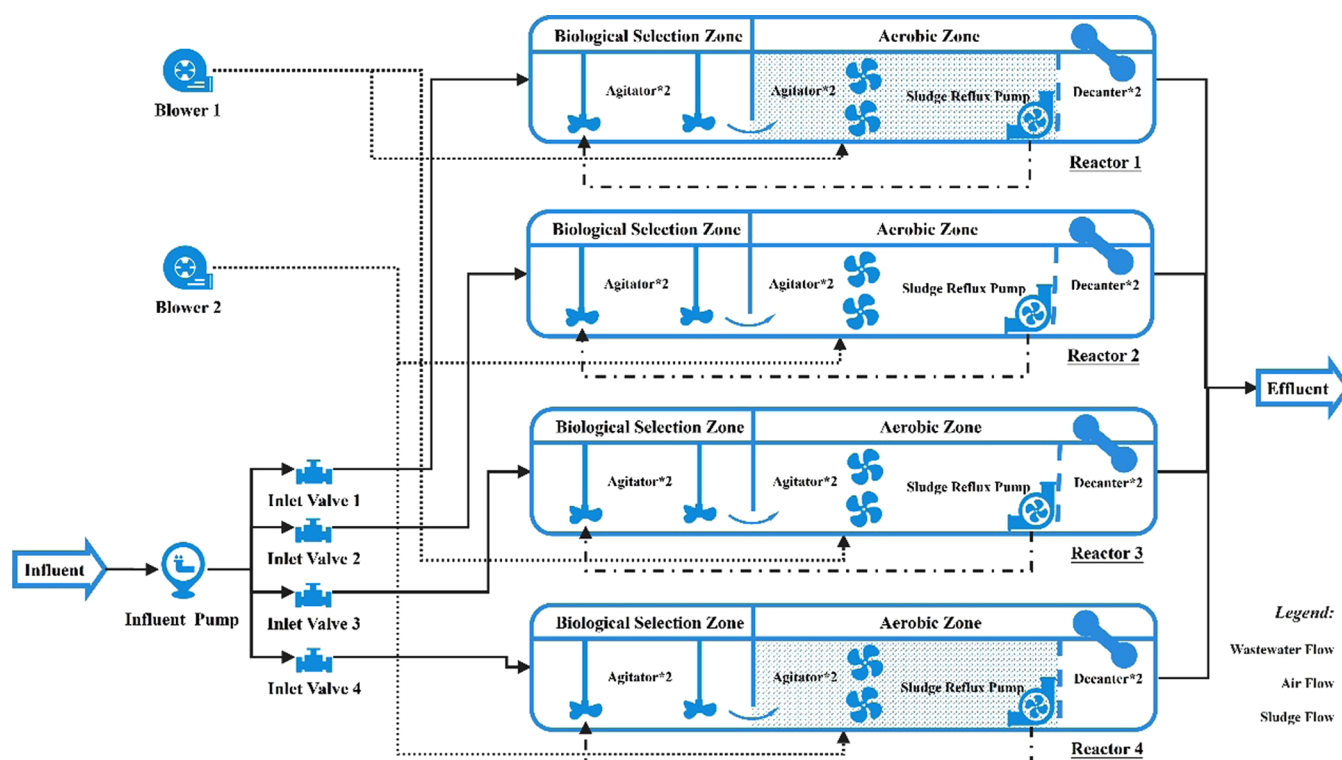


Figure 1. Configuration of the investigated WWTP.

$$\begin{aligned}
 OT_{i,l,m}^f &\leq OT_{i',l,m'}^s \quad \forall (i, i') \in I, i > i', (m, m') \in M, m < m' \\
 l &\in \{\text{"fill", "react", "decant"}\} \quad (12)
 \end{aligned}$$

Equations 11 and 12 prevent reactors sharing the same facility to have any overlap in certain processing stage of the same batch or different batches, respectively. It should be noted that perhaps not all treatment units will be subjected to sequencing constraints caused by resource limitations. Therefore, whether these sequencing constraints are included depends on the specific situations of the WWTP. The general forms of constraints can be adapted; in particular, i , l , and m in eqs 11 and 12 can be specified to avoid overtightening.

3.2.3. Processing Duration Constraints. The end time of a processing stage l in cycle m of reactor i should always be greater than the start time of the same processing stage. The difference between the end time and the start time of a processing stage is defined as the processing duration of that stage. Equation 13 bounds the processing duration of each specific processing stage to its prespecified maximum and minimum times.

$$T_{i,l,m}^{\min} \leq OT_{i,l,m}^f - OT_{i,l,m}^s \leq T_{i,l,m}^{\max} \quad \forall i \in I, l \in L, m \in M \quad (13)$$

3.3. Objective Function. The objective of this model is to minimize the total electricity cost, which is given by eq 14.

$$\begin{aligned}
 \min Z = & \sum_i \sum_j \sum_l \sum_m \sum_y (((CT_{s_{i,l,m,y}} - CT_{f_{i,l,m,y}}) \\
 & \times (Ty_{f_y} - Ty_{s_y}) \times P_y \times N_{j,l}) \\
 & - ((Ts_{i,l,m,y} - XT_{s_{i,l,m,y}} Ty_{s_y}) \times P_y \times N_{j,l}) \\
 & + ((Tf_{i,l,m,y} - XT_{f_{i,l,m,y}} Ty_{s_y}) \times P_y \times N_{j,l})) \quad \forall \\
 & i \in I, j \in J, l \in L, m \in M, y \in Y \quad (14)
 \end{aligned}$$

In the objective function, Z stands for the total electricity cost, P_y represents the TOU electricity price at each predefined time period, and $N_{j,l}$ represents the power of equipment j working at stage l . The auxiliary binary variables $CT_{s_{i,l,m,y}}$ and $CT_{f_{i,l,m,y}}$ are introduced to signify the activation of binary variables $XT_{s_{i,l,m,y}}$ and $XT_{f_{i,l,m,y}}$ respectively, and they are computed by eqs 15 and 16.

$$CT_{s_{i,l,m,y}} = \sum_{y=1}^y XT_{s_{i,l,m,y}} \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (15)$$

$$CT_{f_{i,l,m,y}} = \sum_{y=1}^y XT_{f_{i,l,m,y}} \quad \forall i \in I, l \in L, m \in M, y \in Y \quad (16)$$

4. CASE STUDY

The performance of the proposed MILP model is further illustrated by a case derived from a WWTP in Zhejiang Province, China. The case was programmed and solved using GAMS 24.6.1 with CPLEX 12.6 as the solver on a computer with Intel Core i5-9500 CPU at 3.0 GHz and 8 GB RAM running Windows 10.

Table 1. Rated Power of Major Electricity Consumers in a CAST Reactor Basin

| equipment | processing stage | power (kW) |
|---------------------------------|------------------|------------|
| submersible influent pump | fill | 45 |
| agitator (in the selector zone) | fill and react | 4 |
| agitator (in the aerobic zone) | fill and react | 7.5 |
| sludge reflux pump | fill and react | 7.5 |
| blower | react | 110 |

Table 2. TOU Electricity Pricing of the Local Grid

| scenario | grade | price (¥/(kW·h)) | time periods |
|----------|----------|------------------|---|
| I | on-peak | 1.0397 | 19:00–21:00 |
| | mid-peak | 0.8529 | 8:00–11:00, 13:00–19:00, 21:00–22:00 |
| | off-peak | 0.3539 | 11:00–13:00, 22:00–8:00 _(+1 day) |
| II | on-peak | 1.0957 | 9:00–11:00, 15:00–17:00 |
| | mid-peak | 0.9129 | 8:00–9:00, 13:00–15:00, 17:00–22:00 |
| | off-peak | 0.2901 | 11:00–13:00, 22:00–8:00 _(+1 day) |

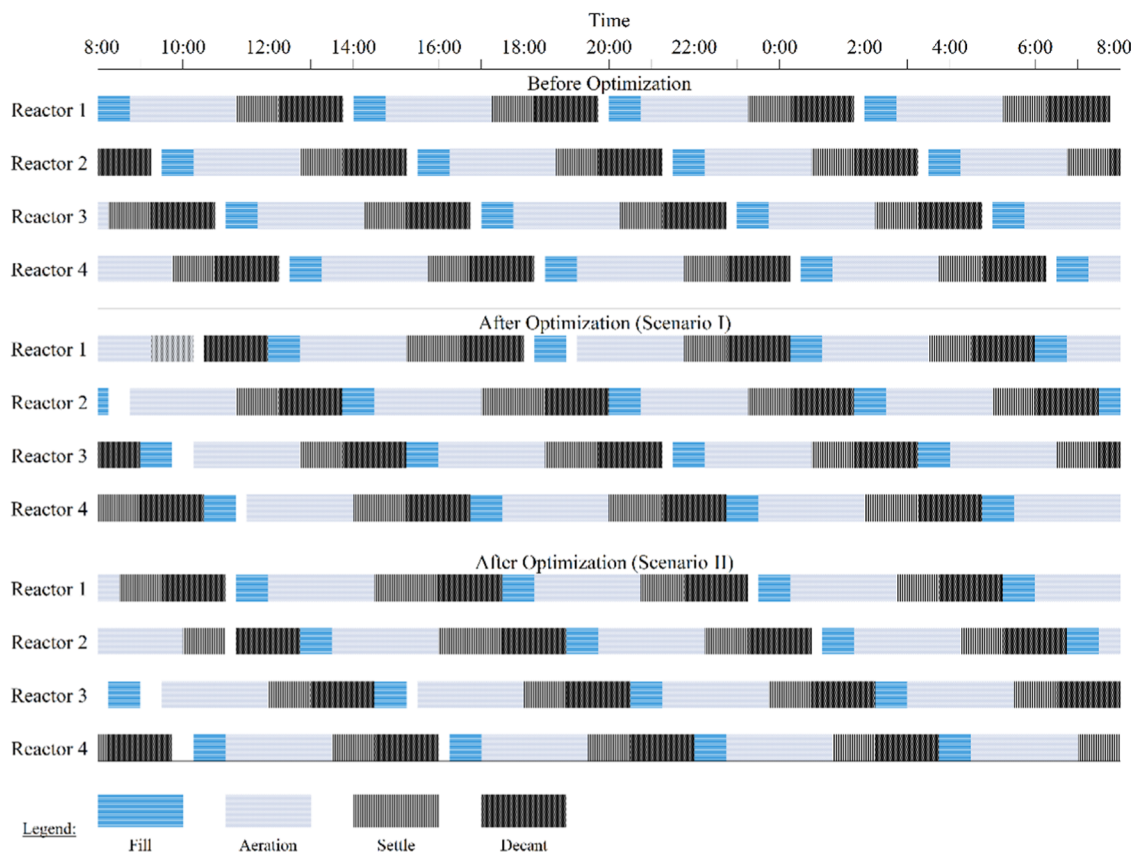
4.1. Case Description. The WWTP investigated employs CAST to treat municipal sewage. As a variant of the generic SBR, CAST has the essential features of plug-flow initial conditions and the complete-mix reactor basin. As shown in Figure 1, the plant has four CAST reactor basins with the same

dimensions. Each CAST reactor basin is divided by a baffle wall into the biological selector zone and the main aeration zone. All reactors are equipped identically with two agitators in the biological selector zone and two agitators, one sludge pump, and two decanters in the main aeration zone. All reactors share one submersible influent pump. Blower 1 is responsible for supplying compressed air to Reactor 1 and Reactor 3, while Blower 2 is for Reactor 2 and Reactor 4.

Each reactor basin intakes 1250 m³ of influent in one batch treatment, and the prespecified times for the stages of fill, react (aeration), settle, and decant are 45, 150, 60, and 90 min, respectively. The WWTP's treatment capacity is 20,000 m³/day, so each reactor must run four cycles within 24 h. At any moment, only one reactor can be in the fill stage, and only one reactor can be in the decant stage. Reactor 1 and Reactor 3 cannot be aerated at the same time, and the same requirement goes for Reactor 2 and Reactor 4.

The rated power of major electricity consumers in the CAST basins is listed in Table 1. Two scenarios with respect to different TOU pricing policies, as given in Table 2, are considered. In reality, the TOU pricing policy in Scenario I was valid until October 2021, and Scenario II became effective since then.

4.2. Optimization Results. The optimal schedules of the batch operation for the WWTP were obtained by implementing the proposed model in the platform of GAMS. The output information includes the optimal start time and the optimal finishing time of each processing stage in each reactor, the electricity consumption in each TOU period, and the minimum electricity cost per day. Figure 2 illustrates the original (before optimization) and the optimal (after

**Figure 2.** Gantt chart for the operational schedules of the WWTP before and after optimization.

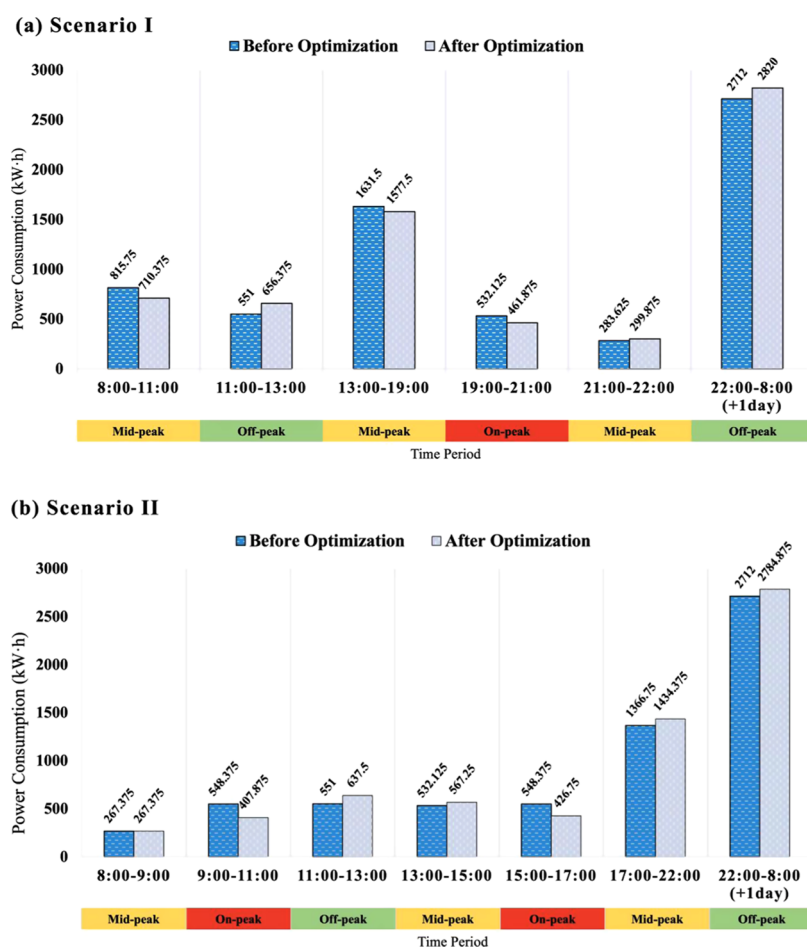


Figure 3. Electricity consumption during each TOU electricity price interval before and after scheduling optimization in (a) Scenario I and (b) Scenario II.

Table 3. Computational Results of the Model

| | scenario I | scenario II |
|--|------------|-------------|
| continuous variables | 5520 | 6290 |
| discrete variables | 3584 | 4090 |
| equations | 10 016 | 11 298 |
| iterations | 702 509 | 434 932 |
| nodes | 7576 | 5618 |
| CPU times (s) | 57.47 | 55.97 |
| electricity cost before optimization (¥/day) | 4037.189 | 4125.875 |
| electricity cost after optimization (¥/day) | 3912.519 | 3954.460 |
| percentage of cost reduction | 3.088% | 4.155% |

optimization) operational schedules for different TOU electricity pricing scenarios. As shown in Figure 3, the electricity consumption during on-peak, mid-peak, and off-peak hours, respectively, changes by -13.20 , -5.24 , and 6.54% in Scenario I and -23.90 , 4.74 , and 4.88% in Scenario II. As shown in Table 3, the electricity cost can be reduced by 3.088 and 4.155% in Scenario I and Scenario II, respectively. These results prove that even though the requirements and restrictions of the WWTP leave a narrow space for scheduling optimization, the proposed model is capable of shifting the electricity consumption from high-price periods to low-price periods as much as possible. Table 3 also indicates that the model can generate optimum solutions very quickly (less than 1 min in this study), which is favorable for the development of

computer-aided control tools embedded with this model in future.

Currently, without changing the treatment processes or configuration of the plant, without adding or retrofitting any hardware, the WWTP can save 4.155% in operating cost simply by carrying out the improved operational schedules generated by the proposed model and still fulfill the requirements of ensuring the treatment capacity and effluent quality in the meantime. Given the huge electricity bill for operating a WWTP in one year, even a reduction of 4.155% means a large amount of expense saved, which is of great significance to the wastewater treatment industry, especially to municipal WWTPs with the nature of public welfare.

4.3. Discussion. TOU is the most common pricing policy that encourages customers to manage energy demand to minimize electricity cost. In China, the National Development and Reform Commission (NDRC) has been improving and promoting TOU electricity pricing for years. Although TOU electricity pricing policies vary from one place to another, there is a nationwide trend to widen the “peak-valley” electricity price difference. In this study, the difference between peak and off-peak prices is larger in Scenario II than in Scenario I, and the electricity cost reduction achieved through scheduling optimization is also greater in Scenario II, as displayed in Tables 2 and 3. It appears that the greater the gap between TOU prices, the more benefits that applying operational scheduling might create. However, it is not clear to what extent

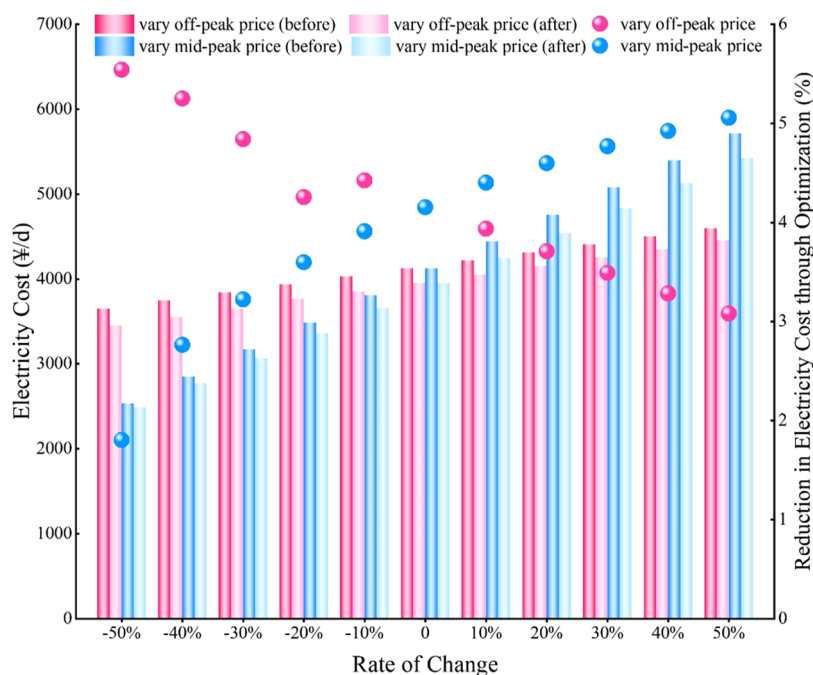


Figure 4. Effects of varying TOU electricity pricing on the electricity cost of the WWTP before and after scheduling optimization.

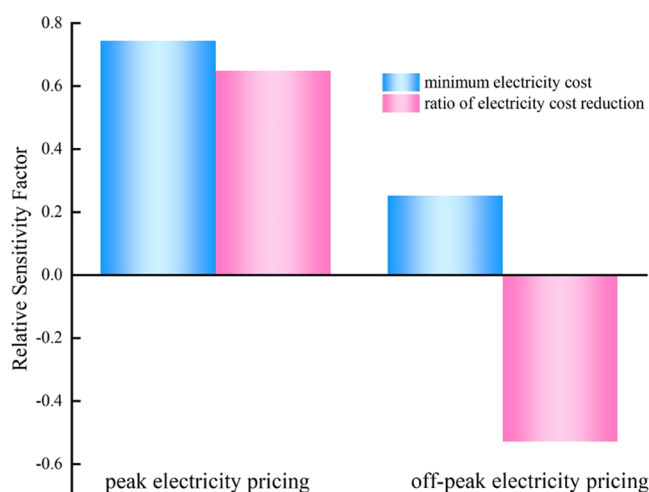


Figure 5. Sensitivity of TOU electricity pricing to the electricity cost and the ratio of electricity cost reduction after implementing scheduling optimization for the WWTP.

the change in TOU prices would affect the optimization result of the model. Moreover, whether increasing the peak price or decreasing the off-peak price has a greater impact on the optimization result is yet to be determined. Therefore, a sensitivity analysis with respect to TOU pricing was conducted.

Scenario II was taken as the base scenario, so its electricity prices and electricity costs were used as benchmarks. The mid-peak price and off-peak price were varied by $\pm 50\%$, respectively, with a step length of 10%. The on-peak price, as recommended by the Chinese government (specifically NDRC) guidelines, was set as 1.2 times the mid-peak price. For every scenario considered, the minimum electricity cost after optimization was exported from model run, while the electricity cost before optimization was calculated based on the operational schedule shown in Figure 2. The relative sensitivity

factor (RSF) was calculated and assessed following the method described by Lenhart et al.²⁹

Figure 4 demonstrates that both increasing peak electricity price and decreasing off-peak electricity price have positive impact on the reduction of electricity cost brought about by scheduling optimization. For instance, under the scenarios in which the off-peak price declines by 40 and 50%, or the mid-peak price rises by 50%, the WWTP can reduce more than 5% in electricity cost if the proposed model is used to optimize operational schedule.

As depicted in Figure 5, the peak electricity pricing and the off-peak electricity pricing are both high-sensitivity parameters²⁹ ($0.20 \leq \text{RSF} < 1.00$) to the electricity cost calculated by the proposed model. The peak pricing is more influential on the final electricity bill than the off-peak pricing. The effectiveness of the scheduling model is mainly evaluated by the ratio of electricity cost reduction. The values of RSF indicate that both the peak pricing and the off-peak pricing are high-sensitivity parameters to the ratio of electricity cost reduction achieved by applying the proposed model. They are roughly equivalent influential, but their impacts are in different directions. Apparently, there is more room to increase the peak electricity pricing than lower the off-peak electricity pricing. The sensitivity analysis confirms that the proposed scheduling model can play a greater role in helping the WWTP reduce the electricity bill as the gap between TOU electricity pricing becomes wider.

From the perspective of a bigger picture, shifting part of the electricity consumption of WWTPs and other energy-intensive industries from on-peak hours to off-peak hours can also reduce the aggregate electric load on the power grid during concentrated power consumption periods, thus contributing to the stability and safety of the local power grid. The past years have witnessed a continuous expansion of the difference between peak load and base load of power grids in many parts of China. The peak load grows significantly, while the base load is less than half of the peak load. To meet the peak load,

the installed capacity of power plants has to be enlarged, and the transmission capacity of distribution grids must be improved. Yet building a large power grid system for covering short-term high demand often leads to low utilization rate and low payback on investment. Therefore, boosting the off-peak electricity consumption of energy-intensive enterprises such as WWTPs through scheduling optimization might help improve the overall efficiency and economy of the local power grid.

Note that the scheduling model established in this study does not essentially reduce electricity consumption for WWTPs. In future work, the scheduling model can be integrated with models simulating biological and/or physicochemical treatment processes so that not only the optimal start time but also the optimal duration of each stage in the treatment process could be solved. The minimization of total makespan is very likely to bring down the total electricity consumption and consequently reduce the electricity cost to a greater extent. In addition, as self-generation power becomes appealing for energy-intensive consumers, the introduction of generation equipment, for instance, solar panels and wind turbines, will certainly complicate the calculation of total electricity cost as well as the scheduling of all units in WWTPs under TOU electricity pricing. To realize a further reduction of both electricity cost and electric power consumption, future research can work on optimizing operational schedules for WWTPs with self-generation equipment.

5. CONCLUSIONS

In this paper, the scheduling problem for the batch operation of a WWTP under TOU electricity pricing is studied. A novel MILP model is established using the event-based continuous-time approach, which considers the task allocation, sequence, and duration of the batch processes. The objective of the model is to minimize the electricity cost of the WWTP. The proposed model can quickly generate an optimal scheduling plan for one-day operation. The WWTP can save 4.155% on its electricity bill simply by carrying out the optimized scheduling plan, without altering the treatment capacity or changing the treatment process. Results of the sensitivity analysis indicate that peak pricing has a stronger impact on the electricity cost than off-peak pricing, but increasing peak pricing or lowering off-peak pricing have a similar impact on the ratio of electricity cost reduction induced by scheduling optimization. The greater the gap between TOU electricity pricing, the more significant effect on reducing electricity cost the model can achieve. Overall, optimizing the time schedule of batch operation is a cost-effective move for the investigated WWTP.

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<https://pubs.acs.org/10.1021/acsomega.2c03302>

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

This work was financially supported by Capacity Building Project of Some Local Colleges and Universities in Shanghai (21010501400) and Shanghai Pujiang Program (20PJ1404600).

NOMENCLATURE

Indices

i reactor
 j equipment
 l stage
 m processing cycle
 y electricity period

SETS

I : set of reactors
 J : set of equipment
 L : set of stages
 M : set of processing cycles
 Y : set of electricity periods

PARAMETERS

$N_{j,l}$: rated power of equipment j working in stage l
 T_{ys} : start time of electricity period y
 T_{yf} : end time of electricity period y
 $T_{i,l,m}$: prespecified processing duration time for stage l of reactor i in cycle m
 P_y : price of electricity period y

POSITIVE VARIABLES

$T_{s_{i,l,m,y}}$: start time for stage l of reactor i in cycle m during electricity period y
 $T_{f_{i,l,m,y}}$: end time for stage l of reactor i in cycle m during electricity period y
 $OT_{s_{i,l,m}}$: optimal start time for stage l of reactor i in cycle m
 $OT_{f_{i,l,m}}$: optimal end time for stage l of reactor i in cycle m

BINARY VARIABLES

$XT_{s_{i,l,m,y}}$: denotes whether start time for stage l of reactor i in cycle m is within electricity period y
 $XT_{f_{i,l,m,y}}$: denotes whether end time for stage l of reactor i in cycle m is within electricity period y

$CTs_{i,l,m,y}$: denotes the sum of $XTs_{i,l,m,y}$ from the 1st electricity period to the y th electricity period
 $CTf_{i,l,m,y}$: denotes the sum of $XTf_{i,l,m,y}$ from the 1st electricity period to the y th electricity period

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