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RESEARCH ARTICLE

Energy Price as an Input to Fuzzy Wastewater Level Control in Pump Storage Operation

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ABSTRACT This paper presents a novel control strategy for pumps in storage tanks that accounts for fluctuations in energy prices. Storage tanks are commonly used in industrial and commercial applications to store and transport large quantities of liquids or gases. The energy consumed by pumping systems can contribute up to 20% of the total electricity usage in industrialized countries. Recent spikes in energy prices have had a detrimental impact on industries reliant on pumping systems, but the growing adoption of renewable energy sources presents new opportunities for energy demand response strategies to balance supply and demand. This study proposes a control strategy that incorporates energy price fluctuations, liquid level, input flow rate, and storm forecasting as input variables. The controller adjusts the pump flow rate every five minutes based on all four inputs. Additionally, this study highlights the environmental advantages of shifting energy usage to maximize renewable energy consumption. The simulation results on a sewer system model demonstrate a 40% reduction in wastewater volume overflow and a 15.5% reduction in energy costs compared to the results of traditional control strategies.

INDEX TERMS Fuzzy control, pumps, storage tanks, sewer system, energy price.

LIST OF SYMBOLS

h	Wastewater level in storage tank.
A_{st}	Area of storage tank.
V_{st}	Volume of storage tank.
$Q_{in,st}$	Input flow rate.
$Q_{out,st}$	Output flow rate.
$Q_{ovf,st}$	Overflow rate.
C_{st}	Constant for weir overflow.
L_{weir}	Length of the weir.
$h_{ovf,st}$	Height of the overflow weir.
P_m	Motor power.
ρ	Fluid density.
g	Standard acceleration of gravity.
ψ	Energy head added to the flow.
η	Efficiency of the pump.
ΔEP	Difference between the current energy price and the mean value for the corresponding day.
k_p	Proportional gain.
k_i	Integral gain.

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I. INTRODUCTION

Pumping systems and storage tanks play a vital role in various industrial and commercial operations. Storage tanks are commonly coupled with pumping systems to store and move large volumes of liquids or gases to different locations for use or further processing. Centrifugal pumps are prevalent in these systems [1], and they are commonly used to temporarily store (buffering) materials such as water, wastewater, fuel, pharmaceuticals, oil, gas, and mineral sludge. These material transfer operations require a substantial amount of electrical energy. Kaya et al. [2] estimated that the demand for energy in pumping systems can account for up to 20% of the total electrical power consumed in industrialized nations.

In recent years, the sudden and substantial spike in energy prices has had a negative impact on many industrial sectors, including those highly dependent on pumping systems. According to the International Monetary Fund (IMF) in [3], the average cost of wholesale electricity in Europe surged by over four times its original value, rising from an average of €35 per megawatt-hour (MWh) in 2020 to approximately €250 per MWh by the end of 2021. This was before the conflict in Ukraine, which further escalated prices, pushing the average wholesale price of electricity to above €500 per MWh in March 2022.

The increasing adoption of renewable energy sources, such as solar and wind power, has the potential to decrease electricity prices in the long term. Still, it also leads to fluctuations in electricity prices throughout the day. This is because the output of renewable energy sources is dependent on weather and seasonal conditions, which can result in variations in supply. For example, solar power output is highest during peak sunlight hours, and wind power output is highest during periods of high wind. This dynamic causes wholesale electricity prices to tend to be lower during periods of high renewable energy output and higher during periods of low output. This creates a dynamic pricing system known as time-of-use pricing, where electricity costs vary depending on the time of day and the demand [4]. While the energy price fluctuation can be challenging for consumers and businesses that require a consistent energy supply, it also presents new opportunities for energy storage and demand response strategies that can help to balance supply and demand.

Storage tanks do not typically require a fixed output flow rate. They are designed to store a large volume of liquids or gases and release them as needed without a fixed output flow rate. Usually, the only requirements are not to overflow and not to let the tank become totally empty. Thus, the material flow rate is adjusted based on the process's specific needs, which allows for flexibility in the system's operation. This characteristic is attractive when it comes to energy price fluctuations: filling and emptying the tank are actions that can be shifted or anticipated depending on how cheap or expensive the energy is at that moment of the day. Automation systems and integration tools enabled by Industry 4.0 can be employed to reduce energy costs in pump storage operations.

The most common type of automatic control for storage tanks follows this simple algorithm: if the water level exceeds an assigned value, the pump turns on; conversely, when the water surface decreases below a minimum value, the pump turns off. In contrast to established methods, this paper proposes a new control strategy for pumps in storage tanks that also considers energy price fluctuation. The study is based on a realistic sewer system model [5], where the pumps are the main energy consumer and their cost is important for the overall budget of this kind of business [6]. This problem is challenging since there is a conflict between shifting the utilization of pumps and not allowing overflow pollutants into the environment. Therefore, two sensors for continuous variables are used in the process and are taken as controller inputs: the level of wastewater in the tank and the tank inflow rate. In addition, two external data sources are included as inputs: weather forecasts and day-ahead energy prices. The controller changes the pump velocity every five minutes based on all four types of input information.

Our proposal differs from other control approaches in that it incorporates the following contributions in an integrated manner: (i) the energy price is actually included as a member function of a fuzzy controller; (ii) there are no fixed values that define a cheap or expensive energy price, and this is instead defined according to the mean price of the current day; (iii) we consider the application of a variable-frequency drive (VFD) to manipulate the pump flow rate; and (iv) control loop integration with IT systems in line with Industry 4.0 practices is used to obtain weather forecasts and day-ahead energy prices. Finally, this study also highlights the advantages from an environmental perspective of shifting the use of energy, maximizing the amount of time during which renewable sources produce most of the energy.

II. MOTIVATION

Postponing an eventual increase in the pump flow rate to avoid expensive energy tariffs is economically and environmentally advantageous. The cost of electricity is the dominant proportion of the total lifecycle costs of a wastewater pumping system, accounting for 34% [7]. Additionally, according to the IPCC report in [8], the generation of electricity and heat accounted for 25% of global greenhouse gas emissions. In addition, assuming there is available capacity in the storage tank, there is no negative impact of temporarily accumulating some wastewater and releasing it at a more reasonable time.

Figure 1 illustrates a typical curve of the amount of electrical energy generation according to the source type and the respective energy prices during one day in Germany. The energy price changes hourly, and there is a great difference between the minimum and maximum prices on the same day. In the sample day illustrated in Figure 1, the maximum value is 500 EUR/MWh at 8 a.m., and the minimum is 147 EUR/MWh at 2 p.m. The two peaks in the maximum price also occur when nonrenewable energy generation types are at their total capacity. In contrast, the minimum price occurs when renewable energy production reaches its maximum generation capacity. Thus, following the lowest energy prices indirectly contributes to a higher percentage of renewable energy consumed. The more renewable energy is produced, the lower the energy prices tend to be.

Due to factors such as government subsidies and fluctuations in commodity prices, renewable energy sources may not always result in lower prices. Nevertheless, various policies and strategies such as carbon emissions pricing, fossil fuel taxation, strict emission standards, and the discontinuation of fossil fuel subsidies have the potential to significantly increase the cost of nonrenewable energy sources, as emphasized in previous research [9].

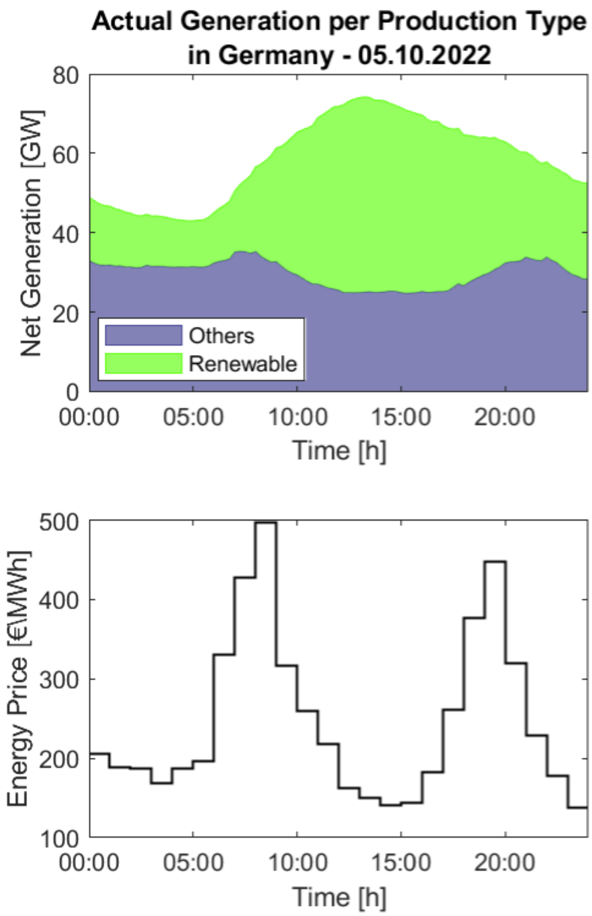

FIGURE 1. The electricity energy production in Germany on 05.10.2022. The total generation according to the production type (top) and the hourly energy price (bottom). Data extracted from ENTSO-E .

III. RELATED WORKS

In this section, we review papers that share two key features in their controller or support decision system: (i) the incorporation of energy tariffs into the computation of storage tank decisions; and (ii) the manipulation of pump equipment. While we do not impose any application site restrictions, we find that the relevant contributions are limited to water distribution networks and sewer systems. Furthermore, our analysis reveals that the majority of works focused on implementation methods fall under the control system and optimization domains.

In [6], a fuzzy controller was introduced to regulate the number of pumps running in a sewer station, accounting for tariff costs that were categorized into three groups: low-cost, normal, and high-cost. To handle these groups, a fuzzy inference system (FIS) was developed for each. The controller chooses the appropriate FIS according to the tariff group on any given day. This strategy was tested through a 24-hour simulation under dry weather conditions, and the results indicated up to 4.3% energy cost savings. A similar approach was presented in [10] and [11], where a rule-based controller was proposed to determine when to switch pumps on and off in a sewer system. The controller was evaluated through a simulation model of a sewer network in Australia, taking into account liquid level and energy market prices. The tariff prices were limited to three groups and fixed for the entire simulation period, and both dry and rainy weather conditions were considered. An energy cost reduction was achieved by increasing the frequency of pump switching, which may impact the equipment's lifespan.

In contrast to control systems approaches, other papers have addressed the use of pumps in storage tanks as optimization problems. An optimization method for the time scheduling of pumps in a water distribution network is introduced by [12]. The energy consumption cost was considered, but only two different tariffs were assumed per day (peak and off-peak). An elegant optimization problem was proposed in [13] to reduce energy costs in a water distribution system (WDS). The cost function was formulated to minimize the water procurement cost and maximize the profit of providing the services. The problem was solved in two steps via a mixed-integer linear programming (MILP) model. The results showed a financial reduction of WDS operation of up to 11.5%. The authors also showed that structural changes on the numbers of tanks and pumps could improve the profit energy gains. As a restriction for regular implementation, the method requires precise forecasts of water demand and electricity prices.

To date, we have found no reports in the scientific literature proposing a controller or support system that simultaneously considers the minimization of energy costs, avoidance of overflows, and use of variable-speed drives (VSDs). Furthermore, we have found no evaluations of such methods for long-term situations, such as seasonal changes in weather and energy prices. Given the practical importance of these considerations, the present work aims to fill this gap in the literature.

IV. THE SEWER STORAGE MODEL

A sewer network is a complex system that comprises various components, such as pipes, pumps, and storage tanks. These components work together to ensure the safe and effective disposal of wastewater and waste products from residential, industrial, and other structures to treatment facilities. The pumps play a critical role in the operation of a sewer system, as they are responsible for moving wastewater through the pipes. The storage tanks, on the other hand, serve as temporary storage reservoirs for wastewater and sewage before it is transported to the treatment facility.

In this study, we used the benchmark model of a sewer system integrated with a wastewater treatment plant in [5], [14], and [15]. Although the model is complete, we only use part of the implemented sewer system, namely, one catchment area and the associated storage tank. The process model was originally coded in Simulink, and it is available to download at github.com/wwtmodels. The next subsections describe the model subparts of interest for this study.

A. CATCHMENT AREA AND INFLOW RATE

In the context of sewer networks, the term ''catchment area'' describes the geographical region that contributes wastewater to a specific segment of the sewer system, typically delineated by the boundaries of the drainage basin or sewershed. In the simulated model utilized in this study, the catchment block generates the wastewater flow rate that feeds the reservoir tank. During dry weather conditions, the sewage flow rate exhibits changes in response to various diurnal, weekly, and seasonal factors. Conversely, during rainfall events, the stormwater flow rate is added to the sewage flow rate. The data analyzed in this paper span a one-year period and are depicted in Figure 2. This figure also gives a detailed representation of selected dry weather days, highlighting a substantial disparity in flow rate amplitude between dry and stormy days. The flow rate value is updated at five-minute intervals, with no control mechanism in place. Consequently, from a control standpoint, the input flow rate represents a measured disturbance.

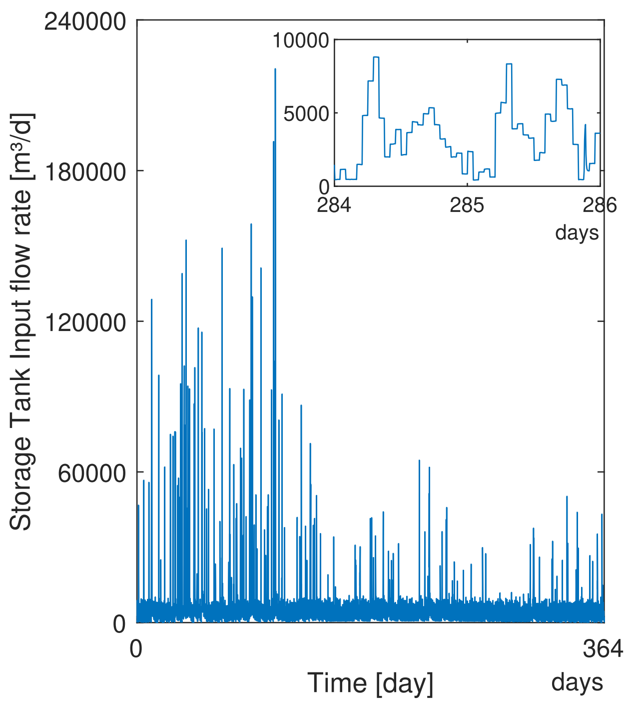

FIGURE 2. Input flow rate for the storage tank in a one-year simulation. The highlighted area shows two regular days with dry weather.

The model utilized in this study also accounts for variations in the levels of different pollutants present in the wastewater flow. These pollutants include suspended solids, ammonium nitrogen, and total phosphorus. The simulation takes into account the original model's values for these pollutants; however, none of these parameters serve as inputs for any controller. As a result, reducing these pollutants in the environment is a consequence of overflow reduction and not a specific control strategy aimed at mitigating them.

B. THE STORAGE TANK

The function of storage tanks in fluid management is to mitigate flow rate variations by serving as a buffer between the input and output streams. Through the storage of excess fluid during periods of production that exceed demand and the release of fluid when demand exceeds production, storage tanks contribute to the maintenance of a consistent and steady supply of fluid. This helps to ensure system stability and minimize disruptions. In the investigated model, the output flow rate ($Q_{out,st}$) is controlled by a pump, while the input flow rate remains uncontrolled. Furthermore, in situations where the fluid level in the tank reaches the height of the weir, wastewater overflows ($Q_{ovf,st}$) into the river. Therefore, the variation in wastewater level in the storage tank with respect to time is described by the following equation:

$$\frac{dh_{st}}{dt} = \frac{1}{A_{st}} \left(Q_{in,st} - Q_{out,st} - Q_{ovf,st} \right), \tag{1}$$

where A_{st} denotes the fixed area of the storage tank.

In this study, pass-through tanks are considered, where the overflow weir is located at the end of the storage tank, meaning that all inflow passes through the tank before reaching the outlet or overflowing into the river. The overflow rate is given by:

$$Q_{ovf,st} = \begin{cases} C_{st} \cdot L_{weir} \cdot \left(h - h_{ovf,st} \right)^{3/2}, & \text{if } h \geq h_{ovf,st} \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

where C_{st} is a constant for weir overflow [$\sqrt{m}/d$], L_{weir} is the length of the weir [m], h is the water level in the tank [m], and $h_{ovf,st}$ is the height of the overflow weir measured from the bottom of the tank [m]. Table 1 presents the main parameters for the storage tank model.

TABLE 1. Main parameters for the storage tank model.

Parameter	Value	Unit	Remark
A_{st}	990	m^2	Area of storage tank.
V_{st}	5000	m^3	Volume of storage tank.
L_{weir}	3	m	Length of overflow weir.
$h_{ovf,st}$	5	m	Height above which overflow occurs.
C_{st}	$1.79 \cdot 10^5$	$\sqrt{m}/d$	Constant for weir overflow.

C. PUMP AND ITS ENERGY CONSUMPTION

For the purposes of this study, we adopt a simplified pump model in which the required flow rate is immediately set by the pump. This assumption is held constant across all controller methods tested, with no variation in pump efficiency. Our objective is not to enhance the equipment's performance, but rather to optimize its utilization in an intelligent manner, thereby taking advantage of opportunities for obtaining low-cost energy. The total motor power required by the pumps is represented by the following equation:

$$P_m = \frac{Q}{24} \cdot \frac{\rho \cdot g \cdot \psi}{36000000 \cdot \eta}, \tag{3}$$

where P_m represents the motor power [kW], Q is the flow rate in [m^3/d], ρ is the fluid density [kg/m^3], g is the standard acceleration of gravity [m/s^2], ψ is the energy head added to the flow, and η is the efficiency of the pump plant as a decimal value. The parameter values utilized in our study are detailed in Table 2.

TABLE 2. Required shaft power for the pump system.

Parameter	Value	Unit	Remark
P_m	50	kW	motor power.
Q	25000	m^3/d	flow rate.
g	9.81	m/s^2	acceleration of gravity.
ψ	10	m	head.
η	0.60	–	pump efficiency.

D. THE ENERGY PRICE

The energy price data for this study were collected from the European Network of Transmission System Operators for Electricity (ENTSO-E). The data represent energy prices in Germany for the year 2022 in the day-ahead trading market. The price varies every hour. Furthermore, we analyzed the source type of the electrical energy with the ENTSO-E dataset, and the types were classified as renewable or nonrenewable.

The total cost of energy in the simulation was calculated using this set of prices for all control strategies evaluated. In particular, the proposed method utilized this set of data as an input for the fuzzy controller. However, instead of feeding the controller the raw price value, the difference between the current price and the mean value for the corresponding day (ΔEP) was used. This approach facilitates the definition of the membership function for the fuzzy controller, as it keeps the limits of the membership function constant and eliminates the need for regular manual maintenance of the controller or any complex method to adapt the controller to seasonal price variations. Figure 3 shows the raw energy price value and the corresponding ΔEP.

V. THE EVALUATED CONTROL STRATEGIES

Three different control strategies for the storage tank system are presented in this section. The first is the most common approach, which is to switch the status of the pump between on and off according to the liquid level in the tank. The second, a proportional-integral (PI) controller, keeps the level of the tank at a set point by manipulating the outflow. The third corresponds to our proposal, in which a fuzzy controller is designed to prevent tank overflow and minimize the operation cost of the pumping system. In this context, only our proposal takes advantage of the day-ahead energy prices.

A. ON-OFF CONTROLLER

The on-off control strategy is a widely used method for the regulation of sewer storage tank networks. This approach entails controlling the pump operation in an all-or-nothing manner based on the level of wastewater present in the storage tank. The implementation of this strategy does not necessitate the use of a variable-speed drive, and it can be implemented through simple ladder logic programming. Despite its simplicity, the frequent switching of pumps can result in increased wear and tear, leading to increased maintenance costs, as reported in [16]. Figure 4 presents a control diagram for the on-off strategy.

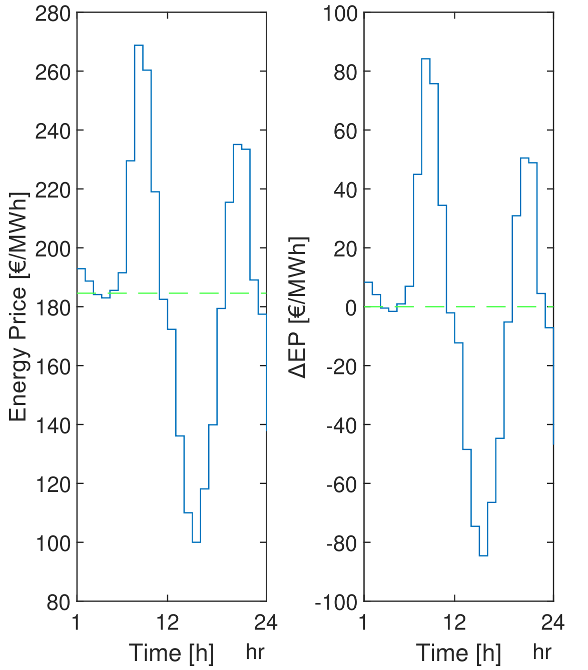

FIGURE 3. The raw energy price (left) and the corresponding difference between the energy price and the average of the day (right).

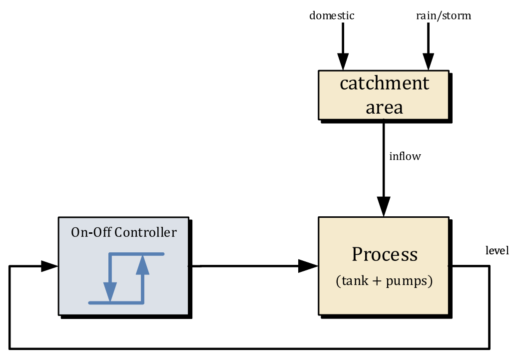

FIGURE 4. Closed control loop for a storage tank with a on-off controller.

Algorithm 1 illustrates a typical sequence of actions for on-off control. The algorithm takes as input a setpoint value, deadband value, and liquid level measurement, and it outputs a pump state that controls the pump's output flow. The algorithm works by continuously measuring the current liquid level and calculating a control signal based on the difference between the current liquid level and the setpoint value. If the current liquid level falls below the setpoint value minus the deadband, the control signal turns the pump off. If the current liquid level exceeds the setpoint value plus the deadband, the control signal turns the pump on. The pump state is then updated based on the control signal, and the pump output flow is controlled accordingly. By using this algorithm, the liquid level in the tank can be effectively maintained within a desired range, while also controlling the pump's output flow to optimize system performance.

Algorithm 1 On-off Control of the Liquid Level in a Tank, With a Pump Controlling the Output Flow Rate

Data: Setpoint: SP, Deadband: DB, Liquid level measurement: LL
Result: Pump state: PS (0 = off, 1 = on)
begin
  Initialize $PS = 0$
  repeat
    Measure the current liquid level: $LL = measure\_liquid\_level()$
    Calculate the control signal: $CS = 0$ (off) or 1 (on)
    if $LL < SP - DB$ **then**
      $CS = 0$
    else if $LL > SP + DB$ **then**
      $CS = 1$
    Update the pump state: $PS = CS$
    Control the pump: $control\_pump(PS)$
  until
end

In an on-off control system, the deadband is important because it defines a range around the setpoint where no action is taken. This helps to prevent rapid switching of the control signal when the measured variable (in this case, the liquid level in the tank) is near the setpoint. Without a deadband, the control signal could rapidly switch between on and off states as the measured variable fluctuates around the setpoint, leading to unstable system behavior and increased wear and tear on the control equipment.

In addition, it is important to note that two pumps are usually used in the storage tank: the duty pump and assistant pump. The first is used more frequently, and the second is turned on to support the duty pump in reducing a prohibitively high liquid level. In this case, two instances of Algorithm 1 run in parallel. The duty pump requires a low-level setpoint and the assistant pump a high-level setpoint. Normally, the deadband for the assistant pump is also greater than the one chosen for the duty pump. Table 3 presents the values for the set point and deadband for the duty and assistant pumps in the simulation.

TABLE 3. On-off controller parameter values for the simulation.

Parameter		Value
Duty pump	Set point	0.95 m
	Deadband	0.05 m
Assistant pump	Set point	3.00 m
	Deadband	0.50 m

B. PI CONTROLLER

Figure 5 illustrates the control diagram of a PI controller for the wastewater level in a storage tank. The PI controller is the most often used algorithm in the regulatory automation layers of industrial control systems due to its simplicity and effectiveness in regulating process variables [17]. It works by continuously measuring the process variable, comparing it to the desired setpoint, and using the error signal to calculate the appropriate control action to bring the process variable back to the setpoint. The proportional term of the PI controller provides an immediate response to changes in the process variable, while the integral term ensures that any steady-state error is eliminated over time. The PI controller considered in this paper is formulated with a Laplace transform:

$$C(s) = k_p + \frac{k_i}{s}, \tag{4}$$

where k_p and k_i are the proportional and integral gains, respectively.

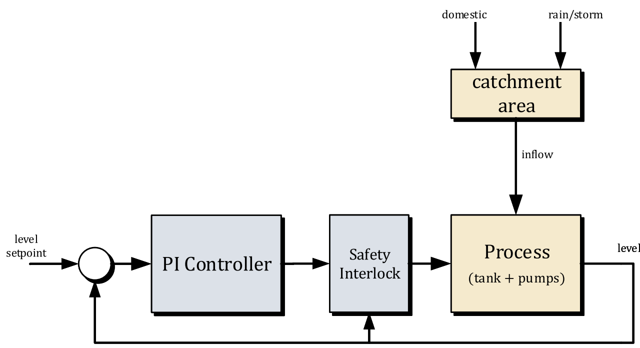

FIGURE 5. Closed control loop for a storage tank with a PI controller and a safeguard system.

The safety interlock block is a control algorithm that helps to ensure safe operation of a pump system by limiting the pump flow rate in response to the liquid level in a tank. The algorithm restricts the pump flow rate in response to the liquid level in the tank, which is measured and transmitted as an input signal to the algorithm along with the desired pump flow rate computed by the PI controller. Based on these inputs, the algorithm produces an output signal representing the required pump flow rate. The algorithm includes two limits - a minimum- and a maximum-level value - to ensure the safe and efficient operation of the system. If the level falls below the minimum value, the algorithm sets the pump flow rate to zero to prevent damage to the system. If the level rises above the maximum value, the algorithm sets the pump flow rate to the maximum to prevent tank overflow. If the level falls within the limits, the algorithm sets the pump flow rate to the desired value. A repeat-until loop structure is implemented to continuously run the algorithm, allowing it to constantly monitor the liquid level and adjust the pump flow rate as required. By implementing the safety interlock block, the pump system can be operated with increased safety and efficiency, reducing the risk of accidents or system damage.

Algorithm 2 Continuous Safety Interlock Block

```
Data: minimumLevel, maximumLevel,
      maximumPumpFlowRate
Input: desiredPumpFlowRate
Output: requiredPumpFlowRate
repeat
    read level;
    if level < minimumLevel then
        requiredPumpFlowRate ← 0;
    else
        if level > maximumLevel then
            requiredPumpFlowRate ←
              maximumPumpFlowRate;
        else
            requiredPumpFlowRate ←
              desiredPumpFlowRate;
        end
    end
    write requiredPumpFlowRate;
until false;
```

The PI and safety interlock parameters designed for this strategy are shown in Tables 4 and 5, respectively. The limits for safety were chosen based on the tank dimensions and assuming that the level set point would be fixed at one meter. Moreover, the gains of the PI controller were computed using the tuning method in [18], which guarantees a smooth control action in a trade-off between robustness and performance.

TABLE 4. PI controller parameters.

Parameter	Value
k_p	-15000
k_i	-500

TABLE 5. Safety interlock block parameters.

Parameter	Value
Minimum Level	0.3m
Maximum Level	4.0m
Maximum Pump Flow Rate	25000 m³/d

C. FUZZY CONTROLLER

The proposed control method considers not only the level in the tank but also the input flow rate and two other external data signals: energy prices and storm forecasts. However, the dynamics of these different signals are not only nonlinear but also difficult to describe using a mathematical model. Consequently, we use a fuzzy logic approach to develop a control strategy that can effectively integrate the different data sources and provide appropriate control signals to the system. By utilizing fuzzy logic, we can account for the imprecise and uncertain nature of the input signals and generate suitable control actions based on the knowledge of an expert in the field. Our approach offers a robust and flexible framework for managing water levels in tanks that can be adapted to a wide range of practical applications.

As depicted in Figure 6, the process diagram shows the integration of a fuzzy controller in the advanced control layer and a PI controller in the regulatory control layer. The fuzzy controller is responsible for managing two process variables: the current input flow rate at the tank and the energy price for the upcoming hours of the day. Based on these input signals, the fuzzy controller determines the optimal set point level that the regulatory controller proposed in the previous subsection should aim at. By combining these two control loops, we aim to achieve maximum system efficiency, resulting in safe and energy-efficient operations. However, in the event of a storm forecast, a low fixed value is used as the level set point to prevent overflow. The design details of this controller are discussed in the following subsections.

1) FUZZY INFERENCE SYSTEM

A fuzzy inference system (FIS) is an artificial intelligence system that uses fuzzy logic to make decisions based on uncertain or imprecise information by converting inputs into fuzzy sets, applying fuzzy rules, and generating a fuzzy output that is then converted into a crisp output. Here, the Mamdani inference method [19] is used in the developed fuzzy inference system. Table 6 presents the selected input and output variables of this fuzzy inference system.

TABLE 6. Variables of the fuzzy inference system.

Input variables	**Output variable**
Input flow rate [m³/d]	Wastewater level set point [m]
Energy price [€/MWh]	

2) MEMBERSHIP FUNCTIONS

The membership function is a crucial component in a fuzzy inference system, as it maps an observed input space to fuzzy sets in a universe of discourse, allowing for the representation and manipulation of uncertainty and imprecision. To define membership functions, critical values are identified for each variable, and suitable curves must be established according to these values. For instance, to define membership functions for the fuzzy inference variables presented in Table 6, critical values of very low, low, normal, high, and very high are identified. Due to the coupling between the variables, trapezoidal membership functions are commonly used, as they can provide more flexibility in representing complex and uncertain relationships between variables. Figures 7 and 8

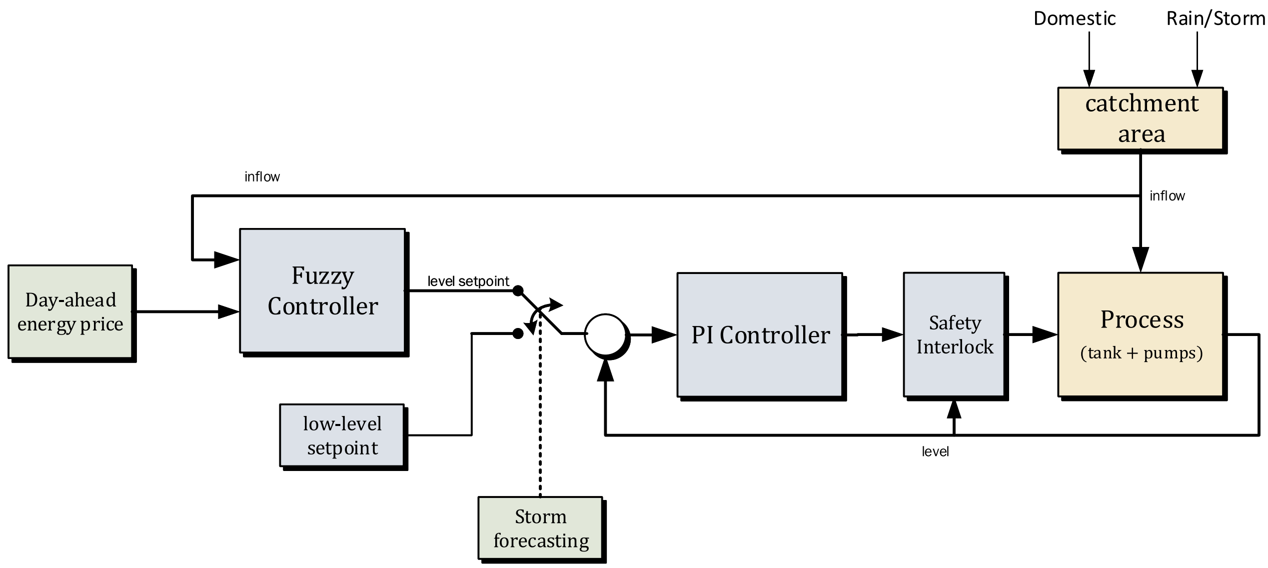

FIGURE 6. **Proposed controller diagram. The yellow boxes represent the process, the blue boxes are the controller components, and the green boxes are the external data.**

illustrate the membership functions for the two inputs. The universe of discourse of the inputs for the fuzzy controller is described as follows.

- Input Flow Rate: The universe of discourse ranges from 0 to 160000 m^3/d, which is the range of historic inflow to the studied tank. As shown in Figure 7, there are five fuzzy sets for this variable. The very-low, low and medium sets cover the daily flow rate fluctuations caused by domestic behavior and weak rains. The sets high and very-high were defined to cover extreme events caused by storms or heavy rainfall. Since lower flow rates are more common during the year, a greater number of sets were reserved for the range 0 to 40000 m^3/d.
- ΔEP: The universe of discourse ranges from -300 to 300 €/MWh. These extremum values were defined based on historical data. According to Figure 8, three sets are defined: cheap, average, and expensive. The cheap set represents prices at which it is viable to use the pump, while the expensive set represents prices at which it is preferable to avoid energy consumption. The average set, which ranges from -20 to 20 €/MWh, represents differences from the daily average price that are considered small enough to be considered neutral. It should be noted that the universe of discourse for the ΔEP membership function is not based on the raw energy price but on the difference between the current price and the daily average price.

The defuzzification interface is responsible for converting the results of the fuzzy inference process into nonfuzzy control actions that can be used by the actual control system. The goal is to obtain a real number that represents the appropriate control action for the system. The membership function for the output variable is illustrated in Figure 9, and the output variables of the fuzzy controller are obtained using

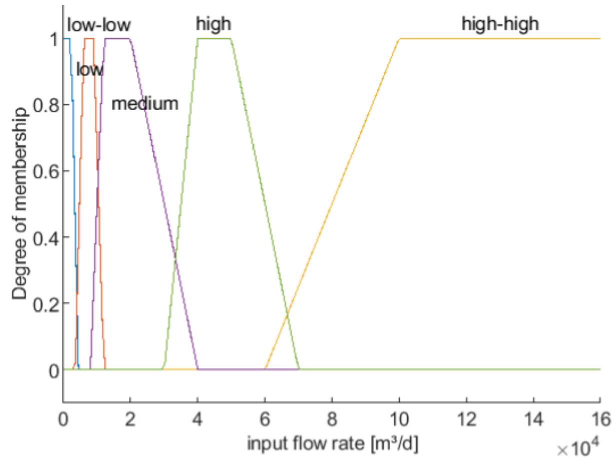

FIGURE 7. **Membership function for the first fuzzy input: input flow rate.**

the centroid (or center of area) defuzzification method. The universe of discourse for the output membership function is divided into five fuzzy sets, ranging from 0 to 4.5m, which represent different levels of the system variable. It should be noted that the limits of safe operation are not considered in the fuzzy system but in the interlock system, as the authors preferred to decouple efficiency aspects from safety requirements. Furthermore, the level set point, which is a reference for the level process variable, takes several minutes to reach zero error (set point equal to the actual tank level), depending on the system dynamics.

3) THE FUZZY RULES

Fuzzy rules are a way to capture expert knowledge about how to combine input variables in order to produce output variables. Each fuzzy rule consists of an antecedent (the "if"

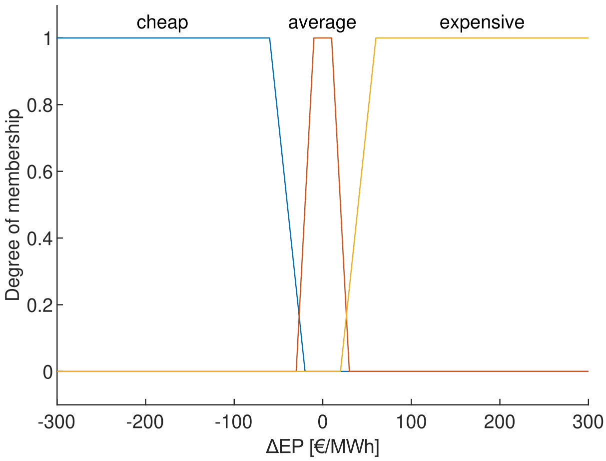

FIGURE 8. Membership function for the second fuzzy input: Δ***EP***.

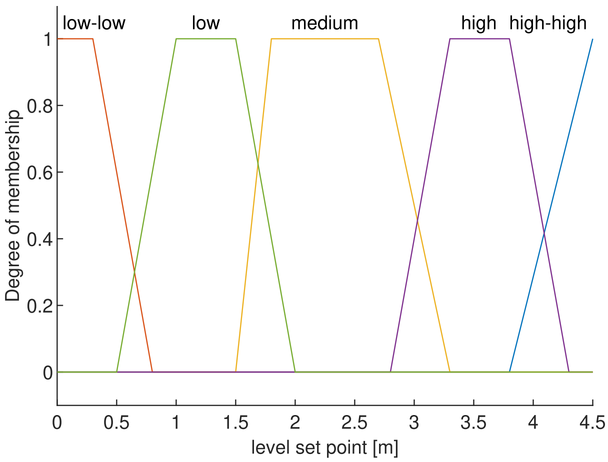

FIGURE 9. Membership function for the unique fuzzy output: level set point.

portion) and a consequent (the "then" portion) connected by the fuzzy operator "and." The antecedent specifies the input conditions in terms of fuzzy sets, while the consequent specifies the output action in terms of a fuzzy set. For example, the rules presented in this system have the form: IF the input variable n is characterized by {very-low, low, normal, high, very-high} AND the input variable m is characterized by {cheap, average, expensive}, THEN the output variable z is characterized by {very-low, low, medium, high, very-high}. The rules are evaluated using a T-norm operator, which in this case is the minimum operator. Figure 10 illustrates the 15 rules developed for this controller.

The rules depicted in Figure 10 demonstrate a direct relationship between the energy price and inflow rate on the one hand and the level set point for wastewater in the tank on the other. Specifically, as the energy price decreases and the inflow rate decreases, the level set point for the tank correspondingly decreases. Conversely, as the energy price increases and the inflow rate increases, the level set point proportionally increases. The overarching objective of these

input flow rate \ ΔEP	cheap	average	expensive
low low	low low	low	high
low	low low	medium	high
medium	low	medium	high
high	low	medium	high high
high high	low	high	high high

FIGURE 10. Fuzzy controller rules.

rules is to utilize the tank as a buffer, with a view to minimizing the usage of the pump during periods of unfavorable economic conditions. As such, the tank temporarily stores wastewater until the energy prices decrease, at which point the wastewater can be released.

4) THE STORM SWITCH

Referring to Figure 6, there is a switch between the output of the fuzzy controller and the set point of the regulatory controller. This switch is subject to storm predictions. In instances where there are no storms predicted, which is typically the case for most of the year, the level set point receives its value from the fuzzy controller output. However, when a storm is predicted to occur the next day, the level set point is fixed at 0.3m. This value represents the minimum level required to empty the tank in anticipation of the heavy rain to follow. This state is maintained for a period of two days, after which the switch returns to the fuzzy controller. In addition, it is worth noting that in this context, a storm is defined as heavy rain that can produce an average input flow rate of 80000m^3/d.

VI. RESULTS AND DISCUSSION

Table 7 presents the outcomes of a one-year simulation for each of the control strategies. The findings indicate that the proposed method outperforms the other two methods in terms of overflow frequency, duration, and volume. Notably, the fuzzy approach effectively prevented nearly 1000 m^3 of wastewater from overflowing when compared to the on-off approach. This success can be attributed to the storm prediction module that enables the system to initiate the emptying of the storage tank one day in advance, thus enhancing the method's efficacy. Minimizing overflow is crucial as tank volume is a cost issue - if we can minimize the overflow by a new control system, we reduce the requirement of expanding the volume capacity of the tanks.

In terms of the overflow quality index, both the PI and fuzzy strategies resulted in significant reductions. However, the PI controller demonstrated an advantage over the fuzzy controller, as the moments when the PI controller allowed for overflow were generally different and coincidentally resulted in higher-quality content within the tank. It is important to note that none of the three methods take into account the quality index in their decision-making processes.

Table 7 also illustrates a minor difference in the energy consumption among the three approaches. This result is anticipated, as the mass transfer among the three scenarios is similar, leading to nearly equivalent pumping efforts. However, the fuzzy controller results in a more economical outcome, with a 15.5% reduction in energy cost, equivalent to savings of over €65000, compared to the baseline. Comparing the PI and on-off approaches, it can be concluded that the introduction of the variable-speed drive alone did not have a significant impact on reducing energy costs. Furthermore, the energy consumed by the pumps in the proposed strategy was predominantly derived from renewable sources, which supports the adoption of an approach that prioritizes environmentally beneficial practices while also minimizing expenses.

To gain a better understanding of the performance of the proposed method, we selected four days (days 6, 7, 8, and 9) of the simulation to compare the results of the PI and fuzzy approaches. During this period, the set point was exclusively determined by the fuzzy controller; that is, the storm predictor and the safety interlocks were not triggered at any time. Figure 11 depicts the level and pump flow rate for the fuzzy approach (blue line) and the PI approach (red line), as well as the inflow and energy price (black curves), which remained the same for all simulated scenarios. On average, the controller changed the set point only four times per day, which provided adequate time for the system to respond. It was expected that the measured level would deviate from the set point, as the purpose of the controller was to adjust the fullness or emptiness of the tank in response to the energy price and input flow rate rather than maintain strict adherence to the set point.

From day six to the end of day seven, we observed a trend of maintaining a high level in the tank (accumulating material) during a period of high energy prices. As soon as the energy prices fell, from the end of day seven to the middle of day eight, the control system began to empty the tank to take advantage of the lower cost. This was despite the fact that the average inflow rate was relatively low and no storms or consistent rains were detected. On day 9, a heavy rain event occurred but did not trigger the storm prediction in the proposed controller. Prior to the rain, the inflow rate was low and energy prices were low, leading the controller to empty the tank. The inflow rate increased rapidly as energy prices also increased, at which point the proposed method held material in the tank and only released it once energy prices returned to a low level at the end of day nine. In contrast, the fixed set point approach utilized high flow rates during the most expensive energy prices of the day. This pattern was repeated throughout much of the year, leading to a noticeable difference in energy costs between the two control methods.

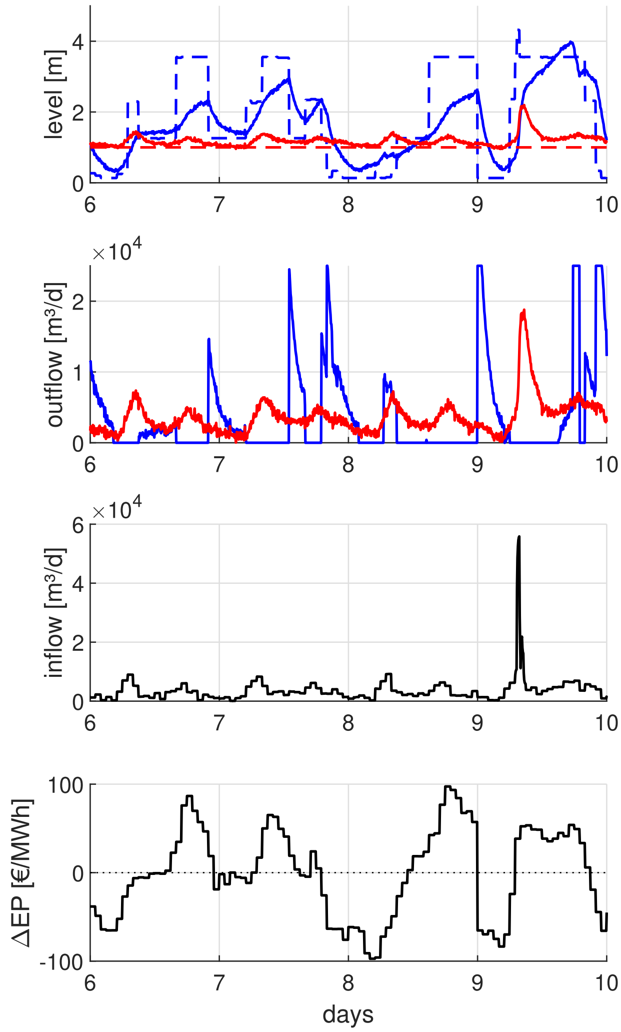

FIGURE 11. Four illustrative days to show the difference between the PI strategy (red line) and the proposed strategy (blue line).The dashed lines are the level set points for each strategy. The inflow and energy price are the same for both strategies evaluated.

Figures 12 and 13 present a heat map depiction of the energy price (ΔEP) and pump flow rate. The total energy expenditure increases with increases in both the flow rate and energy price. The flow rate of the PI controller is primarily concentrated below 10000 m3/day, and ΔEP varies from -200 to 200, which is expected since the PI controller does not consider the energy price. In contrast, the proposed controller achieves a concentration of pump flow rates close to zero while efficiently employing higher flow rates when necessary, resulting in a higher frequency of maximum flow rate values and contributing to the reduction of overflow. Furthermore, the proposed approach imposes higher flow rates when the energy prices are lower ($\Delta EP < 0$). The range of flow rates for the proposed method is wider than that of the other approaches, as the tank is emptied and filled based on energy prices, necessitating high flow rates to compensate the moments when the flow rate was zero.

TABLE 7. Main results from the 364-day simulation comparing the control strategies. The on-off strategy is the baseline.

		Control Strategy				
		On-Off	PI		Fuzzy (Proposed)	
Overflow frequency	[-]	6	5	-17%	4	-33%
Overflow duration	[h]	4	4	0%	3	-25%
Overflow volume	[m³]	2582	1777	-31%	1548	-40%
Overflow quality index	[kg pollutant-units]	2671	1596	-40%	1864	-30%
Energy consumption	[MWh]	1743	1731	-0.7%	1749	+0.3%
Percentage of energy from renewables	[-]	44.6%	44.9%		48.8%	
Energy cost	[€]	423 292	422 914	-0.1%	357 559	-15.5%

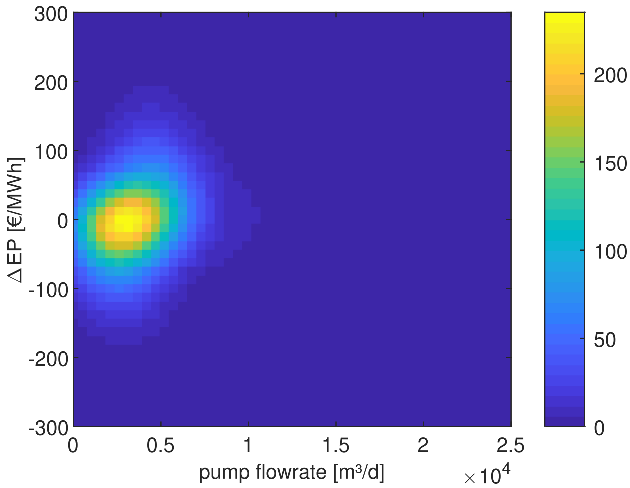

FIGURE 12. 2D heatmap representation of the pump flow rate and energy price difference (ΔEP), where lighter colors indicate higher frequencies. PID strategy.

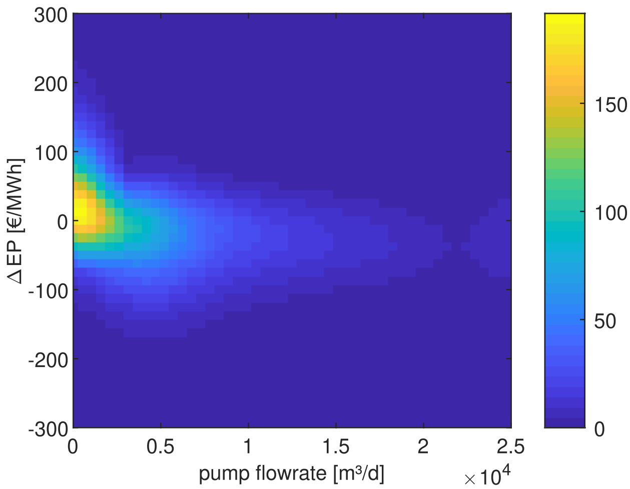

FIGURE 13. 2D heatmap representation of the pump flow rate and energy price difference (ΔEP), where lighter colors indicate higher frequencies. Proposed strategy.

The proposed strategy adjusts the level set point based on the available capacity of the tank, safety considerations, and the energy price. Figure 14 demonstrates that for the majority of the simulation time, the level set point was determined by the fuzzy controller block. During only 9% of the year, the operating mode was switched to prevent overflows caused by storms. The duration of operation in the safety mode was insignificant.

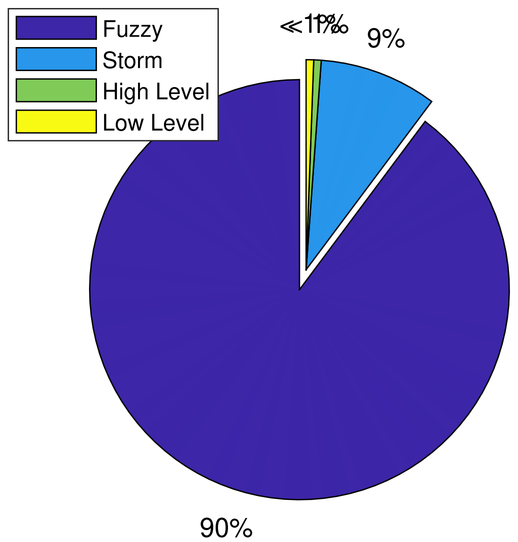

FIGURE 14. The percentage of time during which each block of the proposed controller defines the level set point.

VII. CONCLUSION

In conclusion, the proposed fuzzy control approach provides superior performance in terms of overflow prevention and energy cost reduction compared to the on-off and PI approaches. The implementation of the storm prediction module enables the system to initiate the emptying of the storage tank one day in advance, which significantly reduces the frequency, duration, and volume of overflow. The fuzzy controller's ability to adjust the set point in response to energy prices and input flow rates results in a more economical outcome, with a 15.5% reduction in energy cost compared to the baseline. Overall, the proposed fuzzy control approach is a promising solution for wastewater overflow prevention in urban areas.

For future work, the efficacy of the new strategy will be verified in a sewer network with storage tanks. Additionally, a learning control algorithm will be introduced to optimize the controller parameters, further enhancing efficiency.

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