Stochastic Energy Management of Sustainable Wastewater Treatment Plants in Smart Distribution Systems

by

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Abstract

Wastewater treatment plants (WWTPs), in their current state, appear to be significant energy-consuming entities, harboring enormous but neglected potential for energy production. When proper energy management is applied, they are critical for enhancing the efficiency, sustainability, and resilience of smart distribution systems (SDSs). However, various elements in SDSs with inherent randomness can significantly impact the energy management of WWTPs, including the power output of renewable energy sources (RES), the load demand for electricity, and electricity prices. In this thesis, the stochastic energy management of sustainable WWTPs in SDSs is investigated.

Firstly, a multi-agent stochastic energy management scheme is investigated for SDSs with sustainable WWTPs in order to ensure system voltage quality while minimizing cost. Sustainable WWTPs incorporated in this work comprise various RES such as photovoltaics (PV), hydroelectric, cogeneration, and battery energy storage systems (BESSs). The distribution system operator (DSO) monitors and controls the SDS, which is integrated with BESSs. To achieve optimal operation of sustainable WWTPs while coordinating with DSO and BESSs, this energy management problem is formulated as an interactive partially observable Markov decision process (I-POMDP). The uncertainties associated with incoming wastewater flow, light intensity, and load demand are managed within the framework of the presented sustainable WWTP model. The coordination between the three interdependent entities, i.e., sustainable WWTP, DSO, and BESS, are modelled by I-POMDP featuring interaction and partial observation. An exact solution of the I-POMDP is derived to determine the optimal actions for the sustainable WWTP. Furthermore, to address the complexity arising from the curse of history and dimensionality, a pruning algorithm, based on on-peak and off-peak electricity price analysis, is further presented. The effectiveness of proposed energy management scheme is demonstrated by case studies based on the IEEE 33-Bus Test Feeder, the wastewater flow generated based on end-use model, as well as the historical data of light intensity and load demand.

Additionally, the energy generated by WWTPs can be utilized not only for self-consumption but also for establishing sustainable communities with nearby energy consumers, RES, and energy storage systems within SDSs. A significant reason for establishing a sustainable community in proximity is the economic consideration of the thermal energy characteristics. As electrical energy, thermal energy, and wastewater production events often occur at different timescales, a multi-timescale Markov decision process (MMDP) is utilized to formulate the energy management problem of the sustainable community connected to the smart grid, which includes a sustainable WWTP. The objective is to minimize the total operating cost of the sustainable community while mitigating the impacts on the SDS, considering the randomness of electric loads, wastewater flow, and weather conditions. The proposed energy management scheme is also assessed using the IEEE 33-Bus Test Feeder and incorporates real data on weather conditions, along with wastewater flow information generated through the end-use model.

Preface

The material presented in this thesis is based on the original work by Siyao Ma. As detailed in the following, material from some chapters of this thesis has been published or submitted for publication under the supervision of Dr. Hao Liang in concept formation and by providing comments and corrections to the article manuscript.

Chapter 2 includes the results in the following paper that has been submitted for publication:

- S. Ma, W. Shi, and H. Liang, "Stochastic energy management of sustainable wastewater treatment plants in smart distribution systems," *IEEE Trans. Sustain. Energy*, under review.

Chapter 3 includes the results published in the following paper:

- S. Ma, H. Liang, and M. Bittner, "Multi-timescale stochastic electrical and thermal energy management for sustainable communities with wastewater treatment plants," in *Proc. IEEE CCECE'23*, Sep. 2023.

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Chapter 2

η^{hy}	The overall efficiency of the micro-hydroelectric system
η^{pv}	The overall efficiency of the PV system
η^{rt}	The battery round-trip efficiency
η_c^e	Electrical efficiency of CHP system
η_c^t	Thermal efficiency of CHP system
ι	The battery C-rate
$\mathcal{T}_{u,w,y}$	The time of the water usage event
$\mathcal{U}$	The battery nominal voltage
$\overline{C^{wb}}$	The deployment cost of the battery
Υ	The solid yield from anaerobic reactors
ε	The heating value of methane
φ	The cycle-depth influencing factor of the battery
ϖ_a	The anaerobic reactors' affluent chemical oxygen demand
ϖ_e	The anaerobic reactors' effluent chemical oxygen demand
ϱ_l	The gas loss index in anaerobic reactors or dissolved in the wastewater
ϑ	The percentage of methane in biogas from anaerobic reactors
ξ	The concentration of methane in the produced biogas from anaerobic reactors
ζ	The battery nominal capacity
A^{pv}	The total effective area of the PV system
c^b	The lithium-ion battery's Peukert's constant
$D_{u,w,y}$	The pulse duration of the water usage event
g	The standard acceleration of free fall

h The descending gradient of the micro-hydro turbine

$I_{u,w,y}$ The pulse intensity of the water usage event

L^{pv} The light intensity

p^{bt} Action of the biogas storage unit

p^{b} The battery power exchange

p^{chp} The electrical output of the CHP system

p^{hy} The electrical output of the micro-hydroelectric system

p^{pv} The electrical output of the PV pannels

p^{wt} Action of the wastewater storage unit

p^{wwtp} The WWTP electrical demand

r_t The time-of-use electricity rate

S Wastewater flow rate

S^{bg} The corresponding amount of biogas produced

s^{bt} The available biogas stored in the storage

s^{b} The state of charge of the battery

s^{wt} The wastewater stored in the storage

u The frequency of the water usage events

w The users of water usage events

y The end uses of water usage events

Chapter 3

ξ The specific heat ratio of air

ζ The specific heat capacity of water

p^{com} The electrical loads in the sustainable community

q^{chp} The thermal output of the CHP system

q^{e} The thermal energy generated from the external source of the community

q^{hr} The amount of waste heat recovered from sewage through the heat recovery system

q^{ht} The thermal power exchange

q^{ti} The total thermal energy input

R_{th} The thermal resistance of the building shell

s^{ht} The available thermal energy stored in the storage

T^i The indoor temperature of the building

T^o The outdoor temperature of the building

T_{ifl} The inflow temperature of the heat recovery system

T_{ofl} The outflow temperature of the heat recovery system

Abbreviations

AD Anaerobic Digestion.

BESS Battery Energy Storage System.

BOD Biochemical Oxygen Demand.

CHP Combined Heat and Power System.

COD Chemical Oxygen Demand.

DER Distributed Energy Resource.

DERMS Distributed Energy Resource Management System.

DoD Depth of Discharge.

DSO Distribution System Operator.

FTS Fast Timescale.

I-POMDP Interactive Partially Observable Markov Decision Process.

LCA Life Cycle Assessment.

MDP Markov Decision Process.

MMDP Multi-Timescale Markov Decision Process.

OEB Ontario Energy Board.

PDS Power Distribution System.

POMDP Partially Observable Markov Decision Process.

PV Photovoltaic.

RES Renewable Energy Sources.

SDS Smart Distribution System.

SoC State of Charge.

STS Slow Timescale.

TKN Total Kjeldahl Nitrogen.

ToU Time-of-Use.

uPVC Unplasticized Polyvinyl Chloride.

WWTP Wastewater Treatment Plant.

Chapter 1

Introduction

In this thesis, the stochastic energy management of sustainable wastewater treatment plants (WWTPs) and associated communities in smart distribution systems (SDSs) is investigated. The primary emphasis is on establishing comprehensive mathematical models of the system and developing stochastic energy management algorithms that can operate effectively under various uncertainties.

1.1 Background

Nowadays, most of the world's electricity is produced through fossil fuels, whose supply is limited with adverse impacts on the environment [1]. Meanwhile, the world population is projected to increase to 9.7 billion by 2050, and the trend of urbanization is expected to continue [2]. Because of this fast-growing population, global water use increases rapidly, resulting in large amounts of wastewater production. To this end, WWTPs play a critical role in purifying water. In particular, to serve the fast-increasing population, municipal WWTPs are becoming one major type of energy consumers worldwide [3]. Compared to the other types of energy, electricity contributes the most to wastewater treatment demand, which can be as high as 80%-90% according to various studies [4–6]. For example, in the U.K., the wastewater treatment industry is ranked as the fourth most electricity-intensive sector, with an estimated electricity consumption of 7,703 $GWh/year$ [4]. Similarly, an estimated 3%-4% of U.S. electricity consumption is utilized for the movement and treatment of wastewater [7]. From water companies' perspective, for each WWTP, the electricity cost accounts for up to 60% of its total operating costs [7]. As a result, key participants such as WWTPs need to make changes, who are estimated to use 1%-4% of a country's total electricity output [8]. Meanwhile, heat is the largest energy end-use globally, accounting for nearly half of the world's final energy consumption in 2021 [9]. Among them, residential use is second only to industrial purposes (51%), accounting for as much as 46%. The ensuing greenhouse gas emissions are also enormous. Fortunately, however, WWTPs have great potential for waste heat recovery. For instance, for Austrian wastewater treatment plants, there is a heat surplus of about 600-900 $GWh/year$ which is hardly used at present [10]. Thereby enabling substantial reductions in the utilization of fossil fuels and the emission of greenhouse gases.

With the rapid advancement of sustainable WWTP technologies, wastewater is becoming a valuable resource for renewable energy production. Specifically, one promising solution for renewable power production by WWTPs is micro hydro installation [11]. The main components of the system are the sewage tank, penstock, turbines, and induction generators to ensure the reliable operation of the system. From [12], the uPVC has been recommended as the material for the penstock pipe. There are two common possible types of reaction turbines: Francis turbines and Kaplan turbines (also known as Vortex gravity turbines) [13, 14]. The latter are typically used by sustainable WWTPs as they work more efficiently at low heads and are friendly to dust and sediments. Since WWTPs often have a large amount of wastewater, unlike typical hydroelectric facilities, there is no need for additional civil works for WWTPs such as dams or reservoirs. The installed micro-hydro turbine can generate electricity using the treated water flow before being released. At the same time, the in-plant photovoltaic (PV) system, which includes solar panels (photovoltaic modules), inverter, mounting and racking systems, can convert sunlight into electrical energy. Furthermore, the integration of anaerobic digestion (AD) in existing WWTPs can utilize their spare digestion capacity to generate surplus biogas [15], which is a biological process for treating sludge, in other words, that is, the residual biomass remaining after wastewater has been treated. As an environmentally friendly renewable energy source (RES), the biogas generated from WWTPs can be transformed into electricity and heat, making WWTPs more self-sufficient in terms of energy [16, 17]. Another prominent advantage of WWTP-based biogas is that it is obtained from the AD, requiring no extra fuel cost for electricity and heat production. Biogas tanks are often equipped by sustainable WWTPs for additional flexibility in energy supply. Then, the biogas can be transformed through the cogeneration system into electricity and heat, making WWTPs, and the surrounding community more self-sufficient [16, 18]. Additionally, recent research works indicate that there are three possible places for waste heat recovery from sewage [19]: direct recovery from the building, recovery in the sewer network, and recovery at the WWTP. For consumption points near the WWTP, heat supply from effluent is considered more advantageous than heat extraction in sewers [20, 21]. On this basis, for a WWTP, the heat energy provided by combining the above two heat sources is very considerable. However, due to the particularity of heat energy, it is difficult to transport it over long distances to achieve economic maximization. As a result, connecting potential energy consumers with available excess energy becomes critical. Studies suggest that waste heat can be considered in agriculture, forestry, or low-temperature heating needs in settlements [22]. Building an energy-interconnected community between WWTPs and nearby residents can greatly alleviate the consumption of fossil energy. To better improve the flexibility of the community, energy storage systems can also be installed. All of these together build what we consider a sustainable community, which, in a more specific sense, entails fulfilling the energy requirements of a given locality by means of integrated renewable or cogeneration energy sources [23]. Due to these benefits, in industry, some traditional WWTPs have begun to transform into sustainable ones:

- Sustainable WWTP with water-treatment-independent renewable power generation: Installation of PV array is completed at the city of Pittsfield [24] and Charlemont

Wastewater Treatment Plant [25], Massachusetts, USA, at the Wastewater Treatment Plant Nablus West, Nablus, Palestine [26]; In some particular places, WWTPs have also installed wind turbines, such as at Kensington Wastewater Treatment Plant, Prince Edward Island, Canada [27], at the Fields Point Wastewater Treatment Facility, Rhode Island, USA [28], and at the Dradenau Wastewater Treatment Plant, Hamburg, Germany [29].

- Sustainable WWTP with water-treatment-dependent biogas, micro-hydroelectric, and heat recovery system: Many WWTPs are now starting to use the aforementioned biogas (methane) and micro-hydro power generation in their plants, including North Head WWTP located in Sydney, Australia [30], the Point Loma WWTP in San Diego, USA [31], the Ruhrverband WWTPs (Essen-Kupferdreh WWTP) in North Rhine-Westphalia, Germany [32], and the Clarkson WWTP in Ontario, Canada [33].

In recent years, there are also emerging appearance of WWTPs that combine both categories of sustainable energy production. Examples include the Aquiris Brussels-North WWTP, Brussels, Belgium [34], the Seo Nam WWTP, Seoul, Korea [35], and the Deer Island WWTP, Massachusetts, USA [36].

In addition, real-world examples of sustainable communities are also beginning to emerge. An instance of this can be observed in the announcement of a new project for wastewater heat-recovery by Thames Water and Kingston Council. The project aims to utilize heat obtained from the Hogsmill WWTP located in Kingston upon Thames, southwest London, UK, to supply low-carbon heating to over 2,000 homes in the borough. As stated, up to 7 GWh of low-carbon heat could be supplied per year in the future [37]. Another example can be seen in the design and implementation of heat recovery projects at the recently constructed North Shore WWTP, North Vancouver, British Columbia, Canada, which caters to the inhabitants of the City of North Vancouver, and in New Westminster, where the newly planned Sapperton District is being served. The heat recovery system of the plant is designed to reduce greenhouse gas emissions by 7,200 tonnes per year in

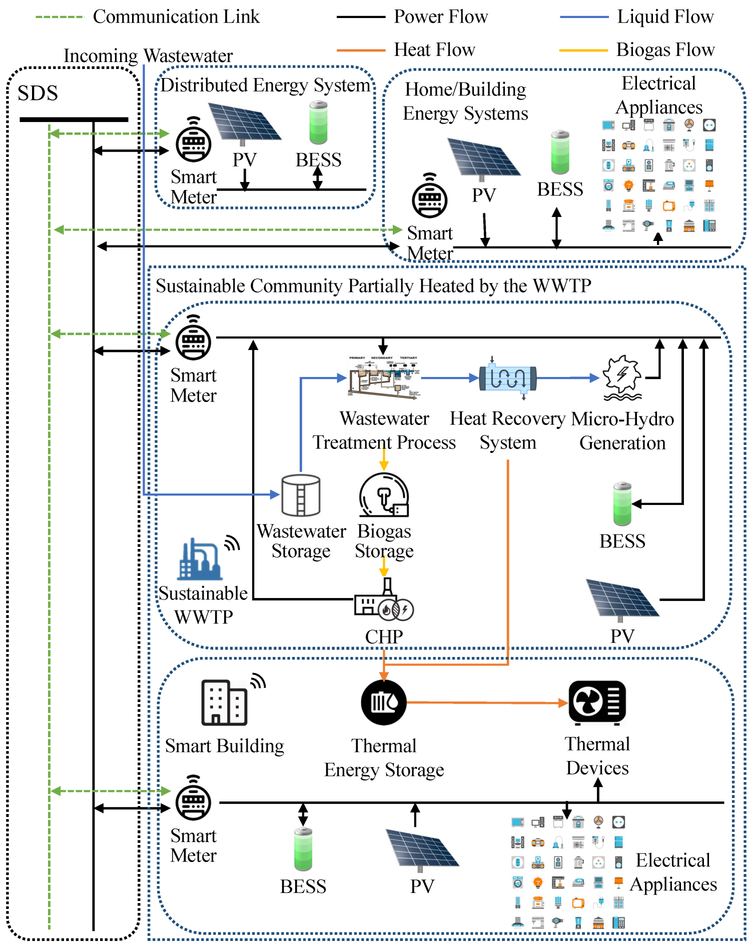

Figure 1.1: The architecture of an SDS with the integrated sustainable WWTP and community.

comparison to the existing Lions Gate plant [38]. The architecture of an SDS with the sustainable WWTP and sustainable community is shown in Fig. 1.1. For the sustainable WWTP, despite the wastewater treatment process, it also contains various storage systems and different renewable energy generation sets. The incoming wastewater is first stored in the wastewater storage. The wastewater treatment process includes primary treatment and secondary treatment, and some have tertiary treatment processes. During the process, sludge from the primary settling tank and balancing tank is sent to the AD process to produce biogas. The product will be initially sent to the biogas tank for storage and later, at an appropriate time, it will be transferred to the CHP system for electricity and heat production. The wastewater will also undergo thorough heat recovery through the heat recovery system and utilize a micro-hydro generation system to produce electricity. Additionally, the facility is equipped with PV panels and installed with batteries to maximize the acquisition of renewable energy and optimize its utilization. The recovered waste heat from the sustainable WWTP will be transported to the nearby smart building. The sustainable WWTP, together with the adjacent smart building, form a sustainable community, that prioritizes energy efficiency and utilization or RES. Within home or building energy systems, battery energy storage systems (BESSs) can effectively store energy from RES, such as PV, and reliably supply electrical demands. All of these are interconnected with the SDS, which integrates various components such as smart meters, sensors, advanced control systems, and RES to enable real-time monitoring, control, and optimization of the power distribution system (PDS). SDS also enables two-way communications, achieved through radio frequency mesh, power line communications, or cellular, allowing for efficient energy management. The implementation of SDS brings numerous benefits, including improved energy efficiency, increased reliability, and lower costs for both utilities and consumers. It is also expected to facilitate the integration of RES into the grid, which can help to reduce the dependence on fossil fuels and mitigate environmental impact. In conventional PDSs, various methods are employed for voltage regulation, including on-load tap changers, reactive power regulators, voltage regulators, capacitor banks, etc. In SDSs, more advanced techniques such as distributed generation and distributed energy storage systems can also be utilized to enhance power regulation. The BESS comprises various components, including the battery management system, battery packs, DC-DC converter, and smart inverter. To enable real-time monitoring and control of the BESS, a controller area network or Internet of Things network is established within each BESS. This network facilitates communication among the various components of the BESS, allowing for efficient and effective management of it. Even though sustainable technologies have been integrated into WWTPs, how to well-utilize these technologies requires extensive scientific research.

In literature, significant works have focused on reducing energy consumption in WWTPs through various approaches such as upgrading plant structures, reducing energy losses, and increasing the efficiency of energy production facilities [7]. Simultaneously, some studies have explored innovative technologies like plasma processing [39] and the Cambi thermal hydrolysis process (CambiTHP) [8]. The energy usage and production of WWTPs have been investigated, resulting in a general estimation of their significance in terms of life cycle assessment (LCA) [40–43]. However, existing literature lacks the consideration of day-to-day temporal energy management given the randomness of wastewater flows. The energy management problem in WWTPs has been extensively studied. This article [44] investigates the optimal operation of the WWTP with the aim of reducing electricity consumption, through developing models for both the incoming wastewater flow and the wastewater treatment process. At the same time, load shifting has been studied in WWTP as another cost-saving method [45–47]. While they [44–47] lack proper coordination with other RES and energy storage devices. Exploring the investment problem of integrating sustainable technologies, specifically PV systems and BESSs, into WWTPs [48], the focus is on determining the optimal sizing of these technologies. However, further investigation is required to determine how to effectively coordinate various RES within WWTPs. Recent research focuses on the energy management of WWTPs within smart grids, taking into account time-varying electricity prices [49–51]. Yet, most studies lack in-depth modeling of the wastewater treatment process and its relationship with energy consumption and production, and they are under deterministic conditions. Therefore, one of the challenges currently faced is how to manage energy while taking into account the stochasticity and the interactions within the wastewater treatment plant and the system. And recently, there have been studies published in the literature regarding heat recovery from WWTPs [52, 53]. Nevertheless, these assessments are typically theoretical in nature, concentrating solely on the heat recovery system and, at most, extending to the plant level. They have not comprehensively modeled the community as a whole in addition to the basic quantitative or qualitative analysis. Meanwhile, in practical energy management for the sustainable community, the regulation of the system environment usually refers to multiple timescales. When operating heating equipment, it is important to consider the slow ramp rate of temperature changes. In contrast, electrical equipment typically operates faster. Moreover, most human water usage behaviors only last for a very short period of time. When all of these processes are taken into account on a single, rapid timescale, the solution dimension becomes too high to be practically valid [54], resulting in significant waste. At the same time, modeling the processes of electricity and water is less accurate when only a single, slow timescale is considered. Therefore, another challenge arises in the context of stochastic energy management for sustainable communities, including WWTPs, where multiple timescales need to be considered to increase accuracy and reduce complexity.

In conclusion, stochastic energy management for sustainable WWTPs and communities in SDSs still requires extensive research efforts. In particular, this thesis will discuss the following two topics:

1. Stochastic energy management of sustainable WWTPs considering interactions with SDSs;
2. Multi-timescale stochastic electrical and thermal energy management for sustainable communities with WWTPs in SDSs.

1.2 General Terms and Definitions

This section aims to establish a precise scope for the conducted research by providing clear definitions of important terms used in this thesis.

1.2.1 Wastewater Treatment Plant with Sustainability

The main objective of a WWTP is to cleanse gathered sewage to ensure its safe discharge into receiving water bodies. Therefore, this means that the goal of high-quality wastewater treatment needs to be achieved. Generally, WWTPs have primary treatment (pretreatment) and secondary treatment, and some have tertiary treatment processes. More specifically, during pretreatment, large material fragments are eliminated to protect the plant's equipment, and to further improve the quality of organic solids. During the primary treatment stage, gravity settling is employed to remove 50%-70% of the overall suspended solids, 65% of the oil and grease, and roughly 40% of the biochemical oxygen demand (BOD) [55]. Secondary treatment, predominantly through biological wastewater treatment methods, involves the elimination of biodegradable organic substances present in a dissolved or suspended state [56]. Tertiary (advanced) treatment is sometimes employed to enhance the cleanliness of the water with additional polishing and disinfection. Before being discharged into the environment, the wastewater undergoes disinfection through processes such as chlorination or UV (ultra-violet). The sludge is treated through the anaerobic sludge digestion process, which fosters the growth of anaerobic bacteria within the sludge digester. After the last treatment, the water can usually reach the drinking water standard.

As mentioned earlier, the WWTP is a very energy-intensive system, but at the same time, its huge energy potential provides itself and even the whole society a strong motivation to explore its sustainability. As the plant itself, upgrading to a sustainable WWTP offers substantial benefits such as reducing reliance on external energy sources, leading to significant cost savings. Moreover, this transition aligns with the government/policymaker's goals of reducing greenhouse gas emissions and fostering social sustainability. The ways of upgrading, to be specific, include but are not limited to installing PV panels, wind turbines, and other RES within the factory premises. At the same time, exploring the use of wastewater treatment processes or their byproducts, such as selling biogas generated during the AD process directly for profit, for combustion heating, or integrating it into the CHP system for both electricity and heat generation. Additionally, incorporating micro-hydropower systems at the outlet points like the chlorination maze exit. Furthermore, implementing heat recovery systems wherever feasible is also a viable upgrading approach.

1.2.2 Smart Distribution System

An SDS is an advanced power distribution system that uses modern communication and information technologies to improve the efficiency, reliability, and sustainability of the power grid [57]. SDS integrates various components such as smart meters, sensors, advanced control systems, and RES to enable real-time monitoring, control, and optimization of the PDS. SDS facilitates two-way communication between the utility and end-users, allowing for real-time monitoring and control of the power flow and voltage levels. SDS incorporates various technologies such as advanced metering infrastructure, distribution automation, and demand response to optimize the distribution of electricity [58].

The traditional PDS faces several challenges, such as limited visibility and control over the distribution network, lack of real-time information, and inefficient use of energy resources. SDS addresses these challenges by integrating advanced technologies and communication systems, providing real-time information on energy consumption, grid performance, and renewable energy generation. SDS has several benefits, including improved energy efficiency, reduced energy consumption, increased reliability, enhanced security, and aid to access to information. SDS can also enable the integration of RES and distributed energy resources (DERs) into the power grid, which can help reduce greenhouse gas emissions and promote sustainable energy use [58]. And with the help of the distributed energy resources management system (DERMS), the distribution system operator (DSO) can manage the grid that is mainly based on diverse and dispersed DERs [59].

1.2.3 Sustainable Community

The sustainable community derives from the related discourse of "sustainability" and "sustainable development". The sustainable community is designed to promote a high quality of life for its residents while minimizing its impact on the natural environment and promoting long-term sustainability. In a narrow sense, it refers to meeting the energy needs of a local community by using renewable energy or high-efficiency cogeneration energy in an integrated way, which can also be regarded as a development of the concept of distributed generation [23]. Here, the sustainable community we envision would provide both sustainable electricity and thermal energy by upgrading traditional WWTPs to novel ones, combined with nearby smart buildings, other RES, and energy storage devices.

1.2.4 Markov Decision Process

A Markov decision process (MDP) is a mathematical framework used to model the decision-making of a dynamic system. It is a stochastic process that considers scenarios where outcomes can partially be random or partially influenced by a decision-maker. Efficient algorithms for the MDP utilizing dynamic programming, linear programming, and compact representations have revolutionized the modeling and solving of problems in various fields such as artificial intelligence, operations research, behavioral sciences, economics, robotics, etc. During each time step, the MDP exists in a specific state, and the decision maker (or the agent) will select any viable action in that state. Subsequently, the MDP undergoes a random transition process based on predetermined transition probabilities, leading it to a new state. In the next time step, the MDP receives a reward based on the immediate reward function that has been defined. The objective of the decision maker (agent) is to choose actions that maximize/minimize a measure of long-term reward accumulation.

1.2.5 Multi-Timescale Markov Decision Process

One expansion of MDP is the Multi-Timescale Markov Decision Process (MMDP), which specifically caters to hierarchically structured sequential decision-making processes. By applying MMDP, decisions at various levels can occur on different timescales. The state and/or control at the higher level cause the lower level MDP dynamics to occur within a finite time horizon that aligns with the higher level's decision-making period. The higher level (slow timescale) decision-making is influenced by the finite horizon value of following a given lower level (fast timescale) policy, which is obtained from the lower level over the decision period of the higher level [60].

1.2.6 Partially Observable Markov Decision Process

The partially observable Markov decision process (POMDP) is an extension of a Markov decision process (MDP) that encompasses a wider range of scenarios with border applications. It assumes that the system dynamics follow an MDP, but the decision maker (agent) lacks direct knowledge of the state. However, it relies on a sensor model along with the underlying MDP. These make it better suited for describing real-world problems. In contrast to the MDP, the POMDP policy maps the history of observations (or belief states) to actions.

Unfortunately, real-life environments are often more complex, or in other words, decision-makers or agents do not exist in isolation most of the time, and their decisions even sometimes influence each other. In response to this, the interactive partially observable Markov decision process (I-POMDP) has been proposed. In essence, its purpose is to enable agents to employ advanced constructs for modeling and predicting the behavior of other agents. In this framework, an agent's beliefs encompass not only the physical state of the environment, but also models of other agents. Similar to a POMDP, its policy involves the mapping of belief states to actions [61].

1.3 Research Definition and Literature Review

This section defines the research problems for the two topics addressed in this thesis. Additionally, it studies the existing literature and discuss previous research efforts.

1.3.1 Stochastic Energy Management of Sustainable Wastewater Treatment Plants Considering Interactions with Smart Distribution Systems

In this research, the stochastic energy management problem is studied for sustainable WWTPs which contain various RES, including PV, hydroelectric, cogeneration, and BESS, inside the SDSs. The objective of this studied optimal energy management problem is to maximize the goal of each participant in the system. Specifically, the utility aims to maximize the voltage quality of the distribution system, while each consumer seeks to minimize their operating costs.

In literature, the energy management problem of WWTPs is studied. In [44,50], the optimal operation of WWTPs is investigated for electricity cost reduction. Both the incoming wastewater flow and the wastewater treatment process are modelled, so that a comprehensive energy management of WWTPs can be achieved. Also, in [45, 62], the energy consumption of WWTPs is reduced through load shifting. The incoming wastewater is stored in a tank first and scheduled to be treated when the electricity price is lower. However, in [44, 45, 50, 62], the sustainable technologies for WWTPs, are not considered. To integrate sustainable technologies into WWTPs, the investment problem of PV systems and BESSs based on optimal sizing is investigated in [48, 63]. Yet, how to coordinate different renewable energy sources in a WWTP during its daily operation still needs further investigation. To address this issue, the energy management of sustainable WWTPs is investigated in [64, 65]. In [64], PV systems and BESSs are coordinated with WWTPs to reduce the energy cost. The RES are well-utilized by considering the uncertainties of sustainable energy and incoming wastewater flow rate. In [65], the feasibility of using biogas as fuel to supply supplemental power to a WWTP is demonstrated. It shows that a well-operated WWTP integrated combined heat and power systems (CHPs) fueled by biogas can transform the WWTP into a self-sufficient facility, reducing its dependence on power supply from the main grid. However, the energy management process in [64, 65] treats the sustainable WWTP as an independent entity without considering its interaction with the power distribution system it connects with. In [51], a co-optimization model is developed to address the power dispatch problem of a PDS embedded with WWTPs. It demonstrates that by considering the operation of PDSs together with WWTPs, better energy management can be achieved with reduced energy consumption. Nevertheless, since the scheme proposed in [51] is deterministic in nature without considering uncertainties, the stochastic nature of sustainable energy can deteriorate its performance. Therefore, how to achieve stochastic energy management of a sustainable WWTP considering interactions with SDSs is still an open issue.

In summary, given existing literature, how to achieve optimal energy management of WWTPs still remains technically challenging, mainly due to the randomness of wastewater influent, and light intensity, as well as the need for coordination with other RES and energy storage systems in the power distribution systems. The future SDSs, which integrate active two-way communication links in the systems, offer a promising solution to coordinate WWTPs with other electric assets for efficient energy management. However, how to develop an optimal energy management scheme by considering the unique features of renewable energy production from the wastewater treatment process still requires extensive research. Furthermore, how to perform energy management for such a multi-agent problem is also an open issue since the SDS involves multiple users with diverse interests arising from their inherent nature, as well as the stochastic nature of the load demand.

1.3.2 Multi-Timescale Stochastic Electrical and Thermal Energy Management for Sustainable Communities with Wastewater Treatment Plants

As mentioned earlier, establishing an energy-interconnected community between WWTPs and nearby residents can greatly alleviate the dependence on fossil energy. Combining other RES such as PV can further enhance the use of clean energy while reducing greenhouse gas emissions. And in order to better improve the flexibility of the community, energy storage systems can also be installed. The collective integration of these constructs what we perceive as a sustainable community. The envisioned sustainable community provides sustainable electricity and heat by upgrading traditional wastewater treatment plants to sustainable ones, combined with proximate smart buildings, other renewable energy sources, and energy storage systems. This also maximizes the benefits of managing the water-energy nexus and reduces the community's carbon footprint.

In literature, considerable substantial works are devoted to the reduction of energy consumption in WWTPs by upgrading plant structures, reducing energy losses, and increasing the efficiency of energy production facilities [3, 7, 66–72]. Some other literature focuses on innovative technologies such as plasma processing and Cambi's thermal hydrolysis process [8, 14, 39, 73, 74]. In several other papers [40–43, 75–83], aspects related to external energy production and the production of chemicals were considered, resulting in a general estimation of the significance of the technology in terms of the life cycle analysis. Authors in [53] and [84] show examples of heat recovery at wastewater treatment plants. The literature related to the energy management problem of WWTP has been presented in Subsection 1.3.1. Recently, there are numerous studies in the literature on BESS and energy management issues related to batteries and grids, such as [85–89].

In summary, given existing literature related to WWTPs, most research works do not address the rationale for day-to-day, temporal energy management, and managing energy as water flow changes. Many of the studies are set in the context of traditional power grids and do not take into account the availability of renewable energy. Existing articles on heat recovery in WWTPs are restricted to theoretical assessments. They focus on the heat recovery system itself, reaching the plant level at most. Until now, there is a lack of articles that comprehensively construct the sustainable community as a block and incorporate realistic and stochastic models, and go beyond simple quantitative or qualitative analyses. In addition, the aforementioned methods for BESS energy management are not directly applicable to SDSs with WWTPs, because, in sustainable WWTPs, electricity consumption and on-site renewable energy generation are closely related.

1.4 Thesis Motivation and Contributions

As discussed above, the development of stochastic energy management of sustainable WWTPs and communities in SDSs still faces great challenges. The detailed motivation and contributions of this thesis are described as follows:

- **Stochastic Energy Management of Sustainable Wastewater Treatment Plants Considering Interactions with Smart Distribution Systems**

  Within the area of literature focusing on energy management in WWTPs, a diversity of perspectives exist. Some studies primarily center on WWTPs without considering their connection with the grid. Some overlook the inherent randomness within the system, and a comprehensive assessment of renewable energy has not been fully explored. At the same time, after upgrading the traditional WWTP to a sustainable one, its energy management becomes more complicated, especially for the coordination and full utilization of its storage system. While there are sufficient studies on energy management in BESS, their direct application here is hindered by the unique characteristics of wastewater treatment plants. In addition, in an SDS with two-way communication networks, exploring how to conduct effective energy management to maximize efficiency while considering interactions with system participants is also a worthwhile area of study. Aiming at the above problems, an energy management scheme is developed for SDSs with sustainable WWTPs capable of generating solar energy, biogas, and micro-hydropower. As other renewable energy sources and energy storage devices may coexist in the SDS, the energy management problem is formulated as an I-POMDP and is solved based on exact and heuristic solutions. In this research work, we have established a comprehensive mathematical model to address the energy consumption and production of sustainable WWTPs according to the stochastic end-use model of wastewater production. Various RES are incorporated for renewable energy generation and electricity cost saving, including not only the PV, but also the energy production from both AD and micro-hydroelectric systems. A multi-agent stochastic energy management problem is formulated for the sustainable WWTP, which integrates the modeling of hydraulics, electricity, chemistry, and bioenergy, as an I-POMDP. The coordination between the sustainable WWTP, the

DSO, and BESSs with uncertainties is addressed. Because of the curse of history and dimensionality, a heuristic solution with the pruning algorithm is proposed to reduce the computational complexity. A reduced set of actions and states will be produced by pruning in advance according to the electricity prices of off-peak and on-peak loads.

- **Multi-Timescale Stochastic Electrical and Thermal Energy Management for Sustainable Communities with Wastewater Treatment Plants**
  As the world moves towards sustainable energy supplies, WWTPs can also be seen as a potential source of renewable energy, which can drastically reduce the use of traditional fossil fuels. A sustainable WWTP can be even more effective when it is properly combined with other energy producers and consumers to form a sustainable community. However, managing energy in that community is technically challenging due to the randomness of wastewater fluency and the need for coordination with other renewable energy sources and energy storage systems. Furthermore, this energy management problem is further complicated by the fact that the flows of wastewater, electricity, and heat occur on different timescales. To address these issues, in this research work, we investigate a sustainable community connected to the SDS, featuring a sustainable WWTP, a smart residential building, and various RES, along with an energy management scheme to improve its efficiency. In particular, a comprehensive mathematical model is established for the sustainable community, which includes PV systems, CHP units, hydroelectric generating sets, heat recovery systems, thermal energy storage, and BESSs, connecting to the SDS. Then, an optimal energy management problem is formulated to minimize the energy costs of the community while maintaining the voltage quality of the SDS. The optimal energy management problem is solved as an MMDP problem, with different timescales used for the modeling of wastewater, electrical, and thermal processes.

1.5 Thesis Outline

This thesis delves into the examination of stochastic energy management in sustainable WWTPs, communities, and their integration into SDSs. MDP-based techniques, designed for addressing sequential decision-making problems in the presence of randomness, are utilized in the context of these stochastic energy management problems. More specifically, in this study, in order to simulate the roles of the participants in the SDS, the interactions between them, and to maximize their corresponding goals, I-POMDP is adopted for energy management. At the same time, the MMDP is employed to account for the various pathways (wastewater, electricity, and heat) found in the sustainable community, each with its own distinct timescale characteristics.

In particular, this thesis comprises four main chapters and is organized as follows:

- **Chapter 1: Introduction** - This chapter begins by providing an introduction to the research background, emphasizing the significance of this thesis. It then proceeds to outline the key terms used throughout the thesis. After defining the research problems, a comprehensive review of pertinent literature is conducted to indicate the challenges associated with each problem. Last but not least, this chapter concludes by presenting the motivation behind each research and its contributions.

- **Chapter 2: Stochastic Energy Management of Sustainable Wastewater Treatment Plants Considering Interactions with Smart Distribution Systems** - In this chapter, a proposed multi-agent stochastic energy management approach for sustainable WWTPs is proposed, which takes into account interactions with SDSs. The SDS is also integrated with BESSs and is monitored and controlled by the DSO. The energy management problem is formulated as an I-POMDP to determine the optimal operation of the sustainable WWTP when coordinating with DSO and BESSs. In addition to the exact solution, an approximation solution based on the pruning algorithm with less computational complexity is also derived. Then through comparison with existing methods, the superiority of proposed schemes is demonstrated.

- **Chapter 3: Multi-Timescale Stochastic Electrical and Thermal Energy Management for Sustainable Communities with Wastewater Treatment Plants** - This chapter investigates stochastic energy management of sustainable communities, which incorporates multiple renewable energy sources, various energy storage devices, an innovative wastewater treatment plant, and a neighboring smart building, connected to SDSs. This optimal energy management problem is formulated based on the MMDP, where the objective is to minimize the total operating cost of the community while mitigating the impacts on the smart distribution system. The proposed energy management scheme is evaluated based on the IEEE 33-Bus Test Feeder as well as real data and modeling.

- **Chapter 4: Conclusions and Future Works** - The main conclusions of the thesis are drawn in this chapter along with suggestions for future works.

Chapter 2

Stochastic Energy Management of Sustainable Wastewater Treatment Plants Considering Interactions with Smart Distribution Systems

In this chapter, a multi-agent stochastic energy management scheme for sustainable wastewater treatment plants is proposed considering interactions with smart distribution systems. The sustainable WWTP incorporates various on-site renewable energy sources, including solar panels, a micro-hydro turbine, and a combined heat and power system fueled by biogas, and BESS. The SDS, which is monitored and controlled by the DSO, is integrated with BESSs. To determine the optimal operation of the sustainable WWTP in coordination with the DSO and BESSs, the optimal energy management problem is formulated as an I-POMDP. The presented sustainable WWTP model addresses the stochastic nature of incoming wastewater flow, light intensity, and load demand. The interaction and partial observation between the three interdependent entities, namely the sustainable WWTP, DSO, and BESS, are modeled using I-POMDP for coordination. An exact solution, which utilizes α-vectors, is developed to ascertain the optimal operating strategy for the sustainable WWTP. In order to decrease the computational complexity, a pruning algorithm is further proposed, based on advanced analysis of off-peak and on-peak electricity prices. The effectiveness of the proposed energy management scheme has been exhibited using the IEEE

33-Bus Test Feeder, the wastewater flow generated based on the end-use model, and the historical data pertaining to light intensity and load demand.

2.1 System Model

In this work, without loss of generality, consider an SDS as shown in Fig. 2.1. In the SDS, a sustainable WWTP is connected to bus 13, two BESSs are located at buses 3 and 10, respectively, and the DSO can conduct SDS operation at the substation. Also, the DSO monitors two smart meters, each situated at buses 5 and 8 for voltage measurement, respectively. There is one smart meter connecting to the sustainable WWTP and each BESS to measure voltages locally. Within the sustainable WWTP, there are various RES. Specifically, there is a wastewater tank used to store wastewater, a biogas tank used to store biogas, a micro-hydro turbine, a CHP system, and PV panels for renewable power generation, and an on-site BESS used to store extra renewable energy. Also, the wastewater treatment process with renewable power generation is as follows: First, the incoming wastewater is stored in the wastewater tank. Then, the wastewater is treated, through the primary and secondary treatment processes, after that biogas can be produced through anaerobic digestion and stored in the biogas tank. In the primary treatment phase, the removal of sizable material fragments serves to safeguard the plant's equipment and enhance the quality of organic solids, through processes such as screening, sedimentation, and sometimes primary clarification. Following the primary treatment, the secondary treatment phase primarily employs various biological methods for treatment. The main objective of this phase is to effectively remove biodegradable organic substances that exist in a dissolved or suspended form within the wastewater. Finally, at the output of the chlorination section in tertiary treatment, the treated wastewater flows into a micro-hydro turbine, and the biogas generated through the anaerobic digestion, associated with sludge treatment, is injected into a CHP system for renewable power generation. Meanwhile, please note that the RES and storage devices mentioned here can be adjusted to fit the specific treatment process in the real plant, which

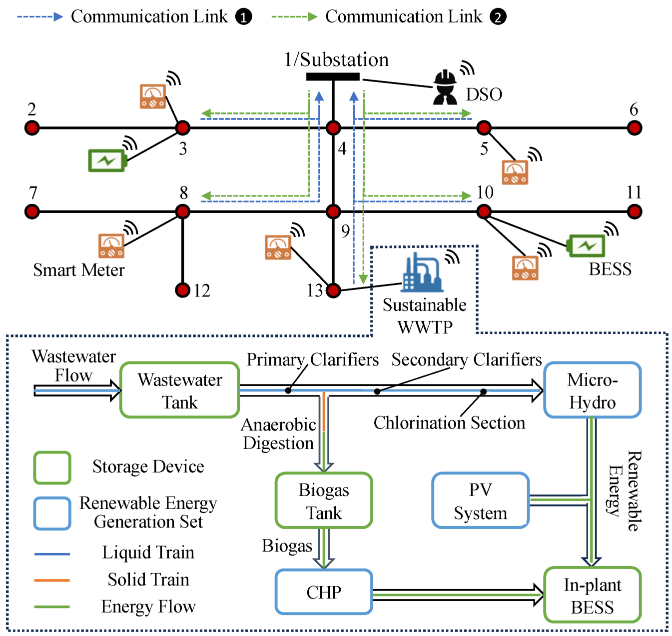

Figure 2.1: An illustration of system model with sustainable WWTPs.

also implies that this work can extend to any facility related to water treatment, such as water treatment plants [90, 91]. Moreover, in the SDS, the information can be transferred through the two-way communication network. The DSO can collect the smart meter data from the physical distribution network through communication link ❶ and share the data through communication link ❷ to the sustainable WWTP and BESSs. The details of the system model are presented and discussed in the rest of this section.

2.1.1 Sustainable Wastewater Treatment Plant Model

Wastewater Flow Model

This end-use model of wastewater production can be defined based on a probability distribution describing the time of arrival, intensity, and pulse duration of the day [92], given by

$$S_t = \sum_{y=1}^{n} \sum_{w=1}^{m} \sum_{u=1}^{f} Z(D_{u,w,y}, I_{w,x,y}, \mathcal{T}_{u,w,y}), \tag{2.1}$$

$$= \begin{cases} \sum_{y=1}^{n}\sum_{w=1}^{m}\sum_{u=1}^{f} I_{w,x,y}, & \mathcal{T}_{u,w,y} \leq T \leq \mathcal{T}_{u,w,y} + D_{u,w,y}, \\ 0, & otherwise, \end{cases} \tag{2.2}$$

where S_t denotes the wastewater flow rate, $D_{u,w,y}$ represents the pulse duration, $I_{u,w,y}$ is the pulse intensity, and $\mathcal{T}_{u,w,y}$ is the time for water usage. At the same time, y summarises all end uses from 1 to n, w counts all users from 1 to m, and u calculates all the busy times for each end-use from 1 to f, which represents the use frequency of user w and application y. Meanwhile, $Z(D_{u,w,y}, I_{u,w,y}, \mathcal{T}_{u,w,y})$ is a block function, with details shown in Eq. (2.2).

Energy Production Model of Biogas

Biogas produced from wastewater treatment process has been widely utilized to provide both electricity and heat. Specifically, during anaerobic digestion, microorganisms break down organic matter in sewage sludge to produce biogas, which is mostly composed of methane (CH_4) and carbon dioxide (CO_2). The biogas production (S_t^{bg}) can be derived based on the chemical oxygen demand (COD) reduction in anaerobic reactors [93], given by

$$S_t^{bg} = S_t \cdot (1 - \varrho_l) \cdot \mathcal{C}, \tag{2.3}$$

where ϱ_l is the gas loss index in the device or dissolved in the wastewater, and $\mathcal{C}$ can be calculated as

$$\mathcal{C} = [(1 - \Upsilon) \cdot \varpi_a - \varpi_e]/(\xi \cdot \nu), \tag{2.4}$$

where Υ is solid yield, ϖ_a and ϖ_e represent the affluent or effluent chemical oxygen demand concentration, respectively, ξ is the concentration of CH_4 in the produced biogas [94], and ν denotes the volume correction factor, which is related to the consumed COD. Then, the produced biogas is injected into a CHP system, combusting for electrical and thermal energy generation:

$$p_t^{ele_{chp}} = S_t^{bg} \cdot \vartheta \cdot \varepsilon \cdot \eta_c^e, \tag{2.5}$$

$$p_t^{thr_{chp}} = S_t^{bg} \cdot \vartheta \cdot \varepsilon \cdot \eta_c^t, \tag{2.6}$$

where ϑ represents the percentage of CH_4 in the produced biogas, ε denotes the heating value of CH_4, and η_c^e and η_c^t represent the electrical and thermal efficiency of the CHP system, respectively.

Micro-Hydro Generation Model

After the wastewater treatment process, the treated water is passed through a micro-hydro turbine mechanically coupled to a generator situated at the outflow. The amount of power that a micro-hydro power generation system can generate is related to wastewater flow (S_t), head (h), and gravity (g) [95], given by

$$p_t^{hy} = \eta^{hy} \cdot S_t \cdot h \cdot g, \tag{2.7}$$

where η^{hy} represents the overall efficiency of the micro-hydro power generation system [13].

PV Power Generation Model

PV power generation is the process of converting energy from the sunlight into electricity using solar panels. The amount of power that the on-site PV system [96] can produce is given by

$$p_t^{pv} = A^{pv} \cdot L_t^{pv} \cdot \eta^{pv}, \tag{2.8}$$

where A^{pv} is the total effective area, L_t^{pv} is solar irradiation, and η^{pv} is the overall efficiency of the PV system.

Load Model of Sustainable Wastewater Treatment Plant

For a well-controlled sustainable WWTP load, the total demand is resulted from the difference between the plant's power consumption (p_t^{wwtp}) and the renewable energy that the plant can produce, including the biomass (p_t^{chp}), micro-hydro (p_t^{hy}), on-site PV (p_t^{pv}) and battery (p_t^b), which can be expressed as

$$p_t = p_t^{wwtp} - p_t^{chp} - p_t^{hy} - p_t^{pv} - p_t^b. \tag{2.9}$$

The WWTP's power consumption is closely related to the wastewater flow rate. And it can be divided into effective energy, as well as ineffective energy:

$$p_t^{wwtp} = S_t \cdot (p^{wwtp,e} + p^{wwtp,i}), \tag{2.10}$$

where $p^{wwtp,e}$ refers to the energy consumption of aeration, anaerobic digestion, pumping, dewatering and mixing, which are directly related to wastewater treatment in a sustainable WWTP. The energy consumption by the other assets such as laboratory, control room and lighting is denoted by $p^{wwtp,i}$.

2.1.2 Battery Energy Storage System Model

The BESS is modelled based on degradation cost and effective charging/discharging power. Specifically, based on Coulomb's law and Peukert's Law, the effective charging power (p_t^b > 0) and discharging power ($p_t^b < 0$) of the BESSs in the WWTP and in the SDS are given by [97]

$$\begin{cases} p_t^b = \mathcal{U}\zeta\omega_t^b[\dfrac{\iota}{\Delta t}], & p_t^b > 0 \\ p_t^b = 0, & p_t^b = 0 \\ p_t^b = \mathcal{U}\zeta\psi_t^b[\dfrac{\Delta t}{\iota}]^{\dfrac{\eta^{rt}-1}{\eta^{rt}}}(\omega_t^b c^b)^{\dfrac{1}{\eta^{rt}}}, & p_t^b < 0 \end{cases} \tag{2.11}$$

where ψ_t^b is the state of battery health, and ω_t^b is the depth of charge/discharge. Due to the degradation of the battery lifetime after each charging/discharging cycle, the state of battery health can be stated as $\psi_{t+\Delta t}^b = \psi_t^b - \bar{e}_{soc}/b_{deg}$.

2.1.3 Stochastic Modeling of Sustainable WWTP in SDS

For a sustainable WWTP, the randomness of the real-time incoming wastewater flow and the light intensity for PV power generation render energy management of the sustainable WWTP stochastic in nature. Also, since the interactions between sustainable WWTPs and SDSs are considered in this study, the uncertainties of load demand in SDSs form another source of randomness. Markov chain with homogeneous state transition probabilities is applied to account for the stochasticity [98]. Specifically, the end-use model generated wastewater flow, the real historical data of time-varying light intensity and load demand can be utilized as sample statistics. Then, the bootstrap method is adopted to randomly resample the original data with replacement to create simulated samples [99]. The estimation of the transition probability can be generated to approximate the true transition probability. Accordingly, we use $P(s^{lt\prime}|s^{lt})$, $P(s^{ww\prime}|s^{ww})$, and $P(s_k^{ld\prime}|s_k^{ld})$ to denote the transition probabilities of wastewater flow, light intensity, and load demand, respectively.

2.2 Formulation of the Stochastic Energy Management Problem of Sustainable WWTP

Traditional WWTPs are large electricity consumers, which can impose significant challenges on the operation of PDSs in terms of voltage quality. Two measures have been taken into account by the industry to alleviate this impact: 1) Upgrading the WWTPs to sustainable ones that can produce amounts of energy on-site to supplement consumption; 2) Coordinating the WWTPs with SDSs integrated with BESSs to achieve a better voltage regulation. However, new challenges also arise. For sustainability, the stochastic nature of sustainable energy introduces high uncertainties in energy management. For coordination, the sustainable WWTP, the DSO, and the BESSs in the SDS are three different entities with respective interests and privacy concerns. Hence, they can only partially observe the state of the system without full access to the comprehensive system information.

To address the above-mentioned challenges, in this section, we formulate the stochastic energy management problem of the sustainable WWTP as an I-POMDP [61]. Compared to traditional POMDPs, I-POMDPs can model multi-agent interactions using interactive states, including beliefs and models of other agents. The stochastic nature of sustainable WWTPs in electricity consumption and renewable energy production is addressed via dynamic state transitions with probabilities. The coordination between the sustainable WWTP, the SDS with BESSs, and the DSO is characterized by the interactions among multiple agents. The voltage information measured by the smart meters is incorporated as observation states and shared through communication links of SDSs. Similar to POMDPs, the policy of I-POMDPs is a mapping from the history of observations (or belief states) to actions. However, the difference is the belief in I-POMDPs considers other agents' beliefs for interactions. In this section, we will present the problem formulation in detail.

2.2.1 Sustainable WWTP Energy Management

The status of a well-controlled sustainable WWTP (agent i) can be characterized as the real-time wastewater flow rate (s^{ww}), the amount of wastewater stored in the wastewater tank (s^{wt}), the amount of biogas stored in the biogas tank (s^{bt}), the state of charge (SoC) of the on-site BESS (s^{wb}), and the light intensity (s^{lt}) for PV power generation. To achieve the optimal energy management, the actions that agent i can take are releasing and injecting wastewater and biogas from and into the tanks (p_i^{wt}, p_i^{bt}), respectively, and discharging and charging the on-site BESS (p_i^{wb}). Since the sustainable WWTP is a participant in the SDS interacting with BESSs (agent j) and the DSO (agent k), the environment that agent i faces should incorporate the information from the SDS, which is the status of load demand (s^{ld}) and the SoC of the SDS-integrated BESS (s^{sb}). However, the sustainable WWTP cannot get full access to all the environmental states, thus the actions that agent i take are based on the observation state, which is the sustainable WWTP bus voltage (V_i^{wwtp}). This bus voltage is locally measured at the sustainable WWTP bus, and can inform the DSO and BESSs in the SDS through communication links. Accordingly, the I-POMDP of agent i of the sustainable WWTP can be described as

$$I - POMDP_i =< IS_i, A, \Omega_i, T_i, O_i, R_i >$$

where $IS_i = S \times \theta_j \times \theta_k$ denotes the set of interactive states. It allows agent i to take actions over the environmental state S, considering the interaction with agents j and k through their models θ_j and θ_k. Also, A denotes the set of joint actions of all agents, Ω_i represents the set of observations of agent i, T_i is the state transition function, O_i represents the observation function, and R_i is the reward function. Specifically, we have

- $s =< s^{ww}, s^{wt}, s^{bt}, s^{wb}, s^{lt}, s^{ld}, s^{sb} >$, $s \in S$;
- $a = a_i \times a_j \times a_k$, where $a_i =< p_i^{wt}, p_i^{bt}, p_i^{wb} >$, $a \in A$;
- $o_i =< V_i^{wwtp} >$, $o_i \in \Omega_i$.

The state transition function of agent i is associated with the operation of various components in the sustainable WWTP, such as the wastewater and biogas tanks, as well as the in-plant BESS. In addition, it is influenced by factors such as the wastewater flow rate and the level of light intensity. This relationship can be represented by the following expression:

$$P(s'|s, A) = P(s^{lt'}|s^{lt})P(s^{ww'}|s^{ww})P(s^{wt'}|s^{wt}, p_i^{wt})P(s^{bt'}|s^{bt}, p_i^{bt})P(s^{wb'}|s^{wb}, p_i^{wb}). \tag{2.12}$$

The observation function of agent i is related to the sustainable WWTP bus voltage measured locally, expressed as

$$P(o_i'|s', a) = P(V_i^{wwtp}|s', a). \tag{2.13}$$

The reward function of agent i is determined by the cost of the sustainable WWTP electricity consumption and the in-plant BESS degradation cost, stated as

$$R_i(s, a) = -r_t T p^{wwtp} - C^{wb}(s^{wb}, p_i^{wb}), \tag{2.14}$$

where r_t is the electricity rate at any time slot t, T is the duration, and C^{wb} is the cost of BESS degraded, given by

$$C^{wb}(s^{wb}, p_i^{wb}) = \frac{e^{[(s_{t+\Delta t}^{wb} + s_t^{wb})/2 - 0.5]\varphi} \overline{C^{wb}}}{\mathcal{D}(\omega_t^{sb})}, \tag{2.15}$$

in which φ represents the cycle-depth influencing factor of the corresponding battery, and $\overline{C^{wb}}$ is the deployment cost of the battery. Furthermore, $\mathcal{D}(\omega_t^{wb})$ indicates the battery life degradation function.

Also, the following constraints are applied:

$$B^l(s^{ww}) \leq s^{ww} \leq B^u(s^{ww}), \tag{2.16}$$

$$B^l(s^{wt}) \leq s^{wt} \leq B^u(s^{wt}), \tag{2.17}$$

$$B^l(s^{bt}) \leq s^{bt} \leq B^u(s^{bt}), \tag{2.18}$$

where B^l and B^u represent lower and upper boundaries for each term, respectively. Constraint (2.16) is to limit the maximum wastewater flow rate of the sustainable WWTP. If the flow exceeds the limit, it will be released directly without treatment. Constraints (2.17) and (2.18) are for the limitation of the storage of the wastewater and biogas tanks. Note that the constraints for the on-site BESS are similar to the ones for the BESSs in the SDS; they will be introduced in the following Subsection 2.2.2.

2.2.2 BESS Energy Management

Given the SoCs of N BESSs integrated into the SDS (s^{sb}), which is a compact notation of vector $\{..., s^{sb,n}, ..., s^{sb,N}\}$, agent j of the BESSs can take discharging and charging actions (p_j^{sb}). Similar to agent i, the environment states S is uncertain to agent j. The information that agent j can observe is the BESS bus voltage (V_j^{sb}). This voltage is locally measured at the BESS bus by smart meters, and can be transferred to the DSO and BESSs in the SDS through communication links. Then, in the I-POMDP of agent i, agent j of the BESSs can be modelled based on its type, given by

$$\theta_j =< b_j, A_j, \Omega_j, T_j, O_j, R_j >$$

where b_j is the belief state of agent j, $a_j =< p_j^{sb} >$, $a_j \in A_j$ is the action of agent j, and $o_j =< V_j^{sb} >$, $o_i \in \Omega_i$ is the observation state. Then, the state transition function of agent j is determined based on the discharging and charging of BESSs, stated as

$$P(s'|s,a) = P(s_j^{sb'}|s_j^{sb}, p_j^{sb}). \tag{2.19}$$

The observation function of agent j is related to the BESS bus voltage measured locally, given by

$$P(o_j'|s',a) = P(V_j^{sb}|s', a_j). \tag{2.20}$$

The reward function of agent j is obtained as the sum of the battery degradation cost and the cost of buying/selling energy from/to the power grid, as

$$R_j(s,a) = -p_k^b r_t T - C^{sb}(s^{sb}, p_j^{sb}), \tag{2.21}$$

where C^{sb} is the cost of battery degraded similar to C^{wb} in Subsection 2.2.1. Also, the following constraints are applied:

$$B^l(SoC) \leq s^{sb} \leq B^u(SoC), \tag{2.22}$$

$$0 \leq |\lambda^{sb}| \leq 1, \tag{2.23}$$

$$-|\overline{I}^{charge}| \leq p_j^{sb}/U \leq |\overline{I}^{disc}|, \tag{2.24}$$

where λ^{sb} represents the change for the SoC, and U indicates the battery terminal voltage. Constraints (2.22) and (2.23) limit the SoC and the changes of SoC of BESSs, respectively. Constraint (2.24) limits the current of charging/discharging.

2.2.3 Smart Distribution System Energy Management

In an SDS, the state that the DSO can observe is the bus voltages measured by the smart meters located at the corresponding buses (V_k^{sm}). Based on this observation, the DSO can take actions on the voltage regulator at the substation by operating the tap changer to change the reference voltage. Therefore, in the I-POMDP of agent i, agent k of the DSO can be modelled based on its type, expressed as

$$\theta_k =< b_k, A_k, \Omega_k, T_k, O_k, R_k >$$

where b_k is the belief state of agent k, $a_k =< p_k^{tp} >$, $a_k \in A_k$ is the action of agent k, and $o_k =< V_k^{sm} >$, $o_k \in \Omega_k$ is the observation state. Then, the state transition function of agent k is determined by operating the tap changer for voltage regulation, given by

$$P(s'|s, a) = P(s_k^{ld'}|s_k^{ld}, p_k^{tp}). \tag{2.25}$$

The observation function of agent k is related to the bus voltages measured by smart meters, stated as

$$P(o_k'|s', a) = P(V_k^{sm}|s', a_k). \tag{2.26}$$

The reward function of agent k is obtained as the penalty of voltage violation, given by

$$R_k(s, a) = -\upsilon \sum \{\max[V_k^{sm} - B^u(V), 0] + \max[B^l(V) - V_k^{sm}, 0]\}, \tag{2.27}$$

where υ is the voltage penalty factor, and the second term is for the penalty of voltage when exceeding the bounds.

2.2.4 I-POMDP Formulation of the Energy Management Problem

When interactions between the sustainable WWTP, the DSO, and the BESSs are considered, the environmental state becomes non-deterministic to each agent. Accordingly, following the I-POMDP, each agent maintains its belief states (represented by b_i, b_j, and b_k). Physically, the belief indicates the likelihood that an agent is in a particular state $s \in S$. In this sense, before taking actions and observations, the agent creates some prior belief (b_i^0, b_j^0 and b_k^0) initially. Then it continuously updates the belief by performing actions and receiving new observations. The belief update function can be stated as

$$b_i'(is_i'|b_i,a_i,o_i)=\beta\sum_{is_i}b_i(is_i)[\sum_{a_j}P(a_j|\theta_j)T_i(s,a_{i,j,k},s')O_i(s',a_{i,j,k},o_i)\times$$
$$\sum_{o_j}O_j(s',a_{i,j,k},o_j)P(b_j'|b_j,a_j,o_j)+\sum_{a_k}P(a_k|\theta_k)T_i(s,a_{i,j,k},s')\times$$
$$O_i(s',a_{i,j,k},o_i)\sum_{o_k}O_k(s',a_{i,j,k},o_k)P(b_k'|b_k,a_k,o_k)], \tag{2.28}$$

where β is the normalization factor. Also, we denote $b_i'=\Psi(b_{i,l},a_i,o_i)$, where Ψ is called the state estimation function in I-POMDPs. It represents the belief update of the agent with its initial belief, action, and observation. Since the objective of the sustainable WWTP is to minimize the cost of electricity consumption while considering interactions with the BESSs and the DSO in the SDS, in this work, the I-POMDP is applied to incorporate other agents' models into the belief state to predict other agents' actions for interactions. Accordingly, each belief in the I-POMDP has an associated value, which is the maximum expected total reward that agent i can gain from the belief state, given by

$$V_i=\max_{a_i\in A_i}\{\sum_{is_i}b_i(is_i)[\sum_{a_j}R_i(s,a_i,a_j,a_k)P(a_j|\theta_j)+\sum_{a_k}R_i(s,a_i,a_j,a_k)P(a_k|\theta_k)]+$$
$$\gamma\sum_{o_i}P(o_i|a_i,b_i)V_i(\Psi_{\theta_i}(b_i,a_i,o_i))\}, \tag{2.29}$$

where the first two terms denote the immediate rewards that can be obtained in b_i, and the last term is the discounted expected total rewards following b_i. Note that the inclusion of models of other agents forms a hierarchical structure. It means that each interactive state is of agent i contains l level of nested beliefs of other agents, whose beliefs are similarly obtained based on the $l-1$ level of nested beliefs of others. In I-POMDPs, this level l is called the strategy level, which indicates the depth of the modelling process. Also, it is evident that when $l=0$, the I-POMDPs are reduced to traditional POMDPs since no other agents' models are included. Accordingly, the finitely nested I-POMDP of agent i can be stated as

$$I-POMDP_{i,l}=<IS_{i,l},A,\Omega_i,T_i,O_i,R_i>$$

where $IS_{i,l}$ denotes the set of interactive states at level l.

2.3 Solution of the Stochastic Energy Management Problem of Sustainable WWTP

The proposed stochastic energy management scheme of sustainable WWTPs considers interactions with SDSs, which are formulated as an I-POMDP, typically computationally intractable. To this end, we first present an exact solution to the problem based on α-vectors, which are hyperplanes defined by policies, to calculate the value function iteratively. In addition, to reduce the computational complexity, a pruning algorithm based on electricity prices is proposed considering off-peak price and on-peak price periods. Specifically, a reduced set of actions and states will be produced by a pruning process according to the electricity prices. In this section, the exact solution and the pruning algorithm are discussed in detail.

2.3.1 Exact Solution Based on α-Vectors

The solution of $I-POMDP_{i,l}$ is the optimal policy π_i^*, which maps the belief $b_{i,l}$ to the distribution over its actions a_i^*. It can be obtained from the value function (2.29), stated as

$$\begin{aligned} a_i^* = \arg\max_{a_i \in A_i} \{ & \sum_{is_{i,l}} b_{i,l}(is_{i,l}) [\sum_{a_j} R_i(s, a_i, a_j, a_k) P(a_j|\theta_{j,l-1}) + \\ & \sum_{a_k} R_i(s, a_i, a_j, a_k) P(a_k|\theta_{k,l-1})] + \gamma \sum_{o_i} P(o_i|a_i, b_{i,l}) V_i(\Psi_{\theta_{i,l}}(b_{i,l}, a_i, o_i)) \}. \end{aligned} \tag{2.30}$$

Since each action is associated with a value of belief state, the value function of the optimal policy for an I-POMDP will be the maximum among all the values. Accordingly, the value function at each time slot t of the horizon can be expressed by α-vectors, which are hyperplanes defined by policies. Then, based on α-vectors [100], the value function can be written as

$$V_i^t = \max_{\alpha \in \Gamma_t} \sum_{is_{i,l}} \alpha(is_{i,l}) b(is_{i,l}), \tag{2.31}$$

where Γ_t is the set of α-vectors. Because the value function in equation (2.31) is composed of the maximum of finite hyperplanes, the value function is guaranteed to be piecewise linear and convex. Note that each α-vector is related to an action, which is the best immediate policy to follow at time slot t. Then, equation (2.29) can be rewritten as

$$
\begin{aligned}
V_i = \max_{a_i \in A_i}\{&\sum_{is_{i,l}} b_{i,l}(is_{i,l})[\sum_{a_j} R_i(s,a_i,a_j,a_k)P(a_j|\theta_{j,l-1}) + \sum_{a_k} R_i(s,a_i,a_j,a_k)\times \\
&P(a_k|\theta_{k,l-1})] + \gamma \sum_{o_i} \max_{\alpha\in\Gamma_{t-1}} \sum_{is'_{i,l}} \{\sum_{a_j} P(a_j|\theta_{j,l-1})[T_i(s,a_{i,j,k},s')O_i(s',a_{i,j,k},o_i)\times \\
&\sum_{o_j} O_j(s',a_{i,j,k},o_i)P(b'_{j,l-1}|b_{j,l-1},a_j,o_j)] + \sum_{a_k} P(a_k|\theta_{k,l-1})[T_i(s,a_{i,j,k},s')\times \\
&O_i(s',a_{i,j,k},o_i)\sum_{o_k} O_k(s',a_{i,j,k},o_i)P(b'_{k,l-1}|b_{k,l-1},a_k,o_k)]\}\alpha(is'_{i,l})b(is_{i,l})\}. \qquad (2.32)
\end{aligned}
$$

From equation (2.32), we can see that the nonlinearity resulting from $V_i(\Psi_{\theta_{i,l}}(b_{i,l},a_i,o_i))$ is addressed. However, since the space of the belief state $b_{i,l}$ is continuous, the calculation of V_i^t is intractable. Then, by utilizing α-vectors, we can iteratively update Γ_t, the set of α-vectors, for value iteration through the following sequence of operations:

- *Step 1*: Generate immediate α-vector sets $\Gamma_t^{a_i,*}$, $\Gamma_t^{a_i,o_i}$, $\forall a_i \in A_i$, $\forall o_i \in O_i$, such that

$$
\begin{aligned}
\Gamma_t^{a,*} \leftarrow & \alpha^{a_i,*}(is) = [\textstyle\sum_{a_j} R_i(s,a_{i,j,k})P(a_j|\theta_{j,l-1}) + \\
& \textstyle\sum_{a_k} R_i(s,a_{i,j,k})P(a_k|\theta_{k,l-1})], \qquad (2.33)
\end{aligned}
$$

$$
\begin{aligned}
\Gamma_t^{a_i,o_i} \leftarrow \alpha^{a_i,o_i}(is) = \gamma \textstyle\sum_{is'_{i,l}} &\{\textstyle\sum_{a_j} P(a_j|\theta_{j,l-1})[T_i(s,a_{i,j,k},s')O_i(s',a_{i,j,k},o_i)\times \\
\textstyle\sum_{o_j} O_j(s',a_{i,j,k},o_i)&P(b'_{j,l-1}|b_{j,l-1},a_j,o_j)] + \textstyle\sum_{a_k} P(a_k|\theta_{k,l-1})[T_i(s,a_{i,j,k},s')\times \\
O_i(s',a_{i,j,k},o_i)\textstyle\sum_{o_k} &O_k(s',a_{i,j,k},o_i)P(b'_{k,l-1}|b_{k,l-1},a_k,o_k)]\}\alpha(is'_{i,l}). \qquad (2.34)
\end{aligned}
$$

- *Step 2*: Create α-vector set $\Gamma_t^{a_i}$, $\forall a_i \in A_i$, by performing cross-sum operation over the observations:

$$\Gamma_t^{a_i} = \Gamma_t^{a_i,*} \oplus \Gamma_t^{a_i,o_1} \oplus \Gamma_t^{a_i,o_2} \oplus ... \qquad (2.35)$$

- *Step 3*: Perform union operation on α-vector sets $\Gamma_t^{a_i}$:

$$\Gamma_t = \cup_{a_i \in A_i} \Gamma_t^{a_i}. \tag{2.36}$$

Then, the value function V_i^t can be calculated based on the α-vector set Γ_t using equation (2.31). Moreover, let Λ^t be the number of α-vector sets at time slot t, and any level contains $|\Xi|$ number of models of other agents. Accordingly, the computational complexity of the exact solution is at most $\mathcal{O}(|S|^2((|A_i|)(\Lambda^t)^{|\Omega_i|} + l|\Xi|))$.

2.3.2 Pruning Algorithm Based on Electricity Prices

To reduce the computational complexity, a pruning algorithm is proposed in this subsection. As mentioned above, the computational complexity of the exact solution depends on the number of α-vectors, which in turn is related to the actions of the agent. Therefore, the idea behind this is that by reducing the action space, it becomes possible to decrease the number of α-vectors, thus resulting in a reduction in computational complexity. By observing the value function, we come to realize that reward is a crucial component. Further analysis of Eq. (2.14) or (2.21) reveals that the reward function of agent i of the sustainable WWTP or agent j of the BESSs in SDS is sensitive to electricity prices (r_t). Hence, the actions can be pruned based on electricity price analysis. Specifically, under off-peak and on-peak periods, the possible actions can be determined in advance as follows:

- During off-peak price periods, the biogas tank (p_i^{bt}) tends to remain unchanged or store the produced biogas. The wastewater tank (p_i^{wt}) tends to remain unchanged or try to use up the stored wastewater. Both BESSs (p_i^{wb}, p_j^{sb}) tend to keep the SoC unchanged or use cheap electricity for charging;

- During on-peak price periods, the possible actions are exactly the opposite. The biogas tank (p_i^{bt}) will remain the same or use as much previously-stored biogas as possible to generate renewable energy. The wastewater tank (p_i^{wt}) tends to maintain no operation or store the incoming wastewater as much as possible. The batteries (p_i^{wb}, p_j^{sb}) will remain silent, or try to provide as much energy as possible.

In short, we will prune in advance the actions that may not be chosen, and the states that may not be reached, as shown in **Algorithm 1**. These pruned selectable action sets can then be used in the value iteration to find the optimal solutions in the I-POMDP. Such preprocessing will result in significant savings in computational time, required memory, etc. Specifically, by using the pruning algorithm, the set of optional actions can be reduced to $|\hat{A}_{i,j,k}|$. Therefore, we will instead only need at most $\mathcal{O}((|\hat{A}|)(\Lambda^t)^{|\Omega|} + l|\Xi|)$ alpha vectors to solve the I-POMDP$_{i,j,k,l}$. And significant computational savings will be obtained for the case where $|\hat{A}_{i,j,k}| << |A_{i,j,k}|$.

Algorithm 1 Pruning algorithm based on electricity prices

Output: Selectable actions $\hat{a}_{i,j,k,l}$

```
for t ∈ T do
    if t = t (r_t = \overline{r_t}), or t = t (r_t = \underline{r_t}), then
        Pruned out unselectable actions, as well as unreachable states (i.e. a_{i,j,k,l} → \hat{a}_{i,j,k,l})
    else
        The sets of possible actions to choose remain the same (i.e. \hat{a}_{i,j,k,l} = a_{i,j,k,l})
    end if
end for
return Agent i's, j's, k's selectable action sets \hat{a}_{i,j,k,l}
```

2.4 Case Study

In this section, the effectiveness of the stochastic energy management of sustainable WWTPs considering interactions with SDSs is demonstrated based on the IEEE 33-Bus Test Feeder. Also, comparative studies are conducted to validate the advantages of the proposed method.

2.4.1 Test System Setup

For the case study, a PC with an Intel CORE i7 CPU and 16 GB RAM is selected as a test platform. In the SDS, the sustainable WWTP is connected to bus 8, one BESS is installed

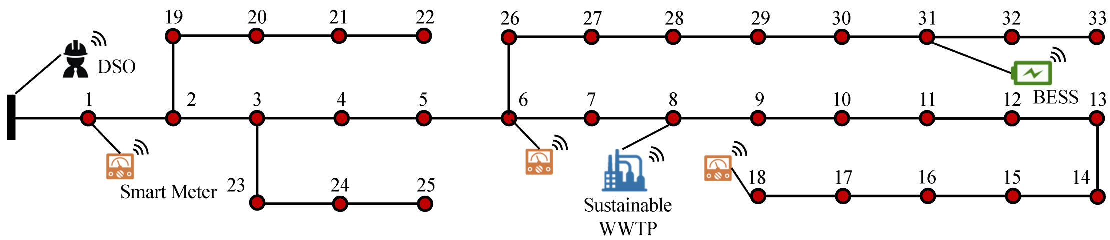

Figure 2.2: An illustration of the IEEE 33-Bus Test Feeder with the sustainable WWTP.

at bus 31, and three smart meters are located at buses 1, 6, and 18, respectively, monitored by the DSO. All other buses in the SDS are residential loads. The lower and upper voltage bounds are 0.95 p.u. and 1.05 p.u., respectively. The historical light intensity and load demand data are derived from [101] and [102], respectively. For wastewater flow rates, frequencies of the end-uses including shower, toilet, bathtub, kitchen faucet, bathroom faucet, outside faucet, washing machine, and dishwasher, are modelled using the binomial, Poisson, and negative binomial distributions, respectively. Samples of the generated wastewater flow results with all eight end-uses for different populations are shown in Fig. 2.3. Due to diverse diurnal patterns among populations, as can be observed from the figure, water consumption patterns vary. However, they all exhibit two distinct water usage peaks, and due to the characteristics of water consumption behaviour, these peaks do not necessarily coincide with peaks in electricity usage. This also demonstrates the enormous potential of using WWTPs to assist in regulating power consumption and production in distribution systems. The household composition is obtained from the 2001 British census [103]. In addition, the net head for the micro-hydropower generation system is set to 2.8 m [11]. The dimensions of the wastewater and the biogas tanks are 300 m^3 [104, 105] and 280 m^3 [106], respectively. The charge and discharge range of BESS are 0.1 to 1, respectively, with a capacity of 140 kWh. The energy management is implemented over five weekdays. The discount factor γ is set to 1 for such a finite period. At the beginning of energy management, it is assumed that both the wastewater and biogas tanks are empty, and BESSs are fully charged. Moreover, the electricity prices used here are the Time-of-Use prices set by the Ontario Energy Board since November 1, 2021 [107]. Specifically, the on-peak price time is from

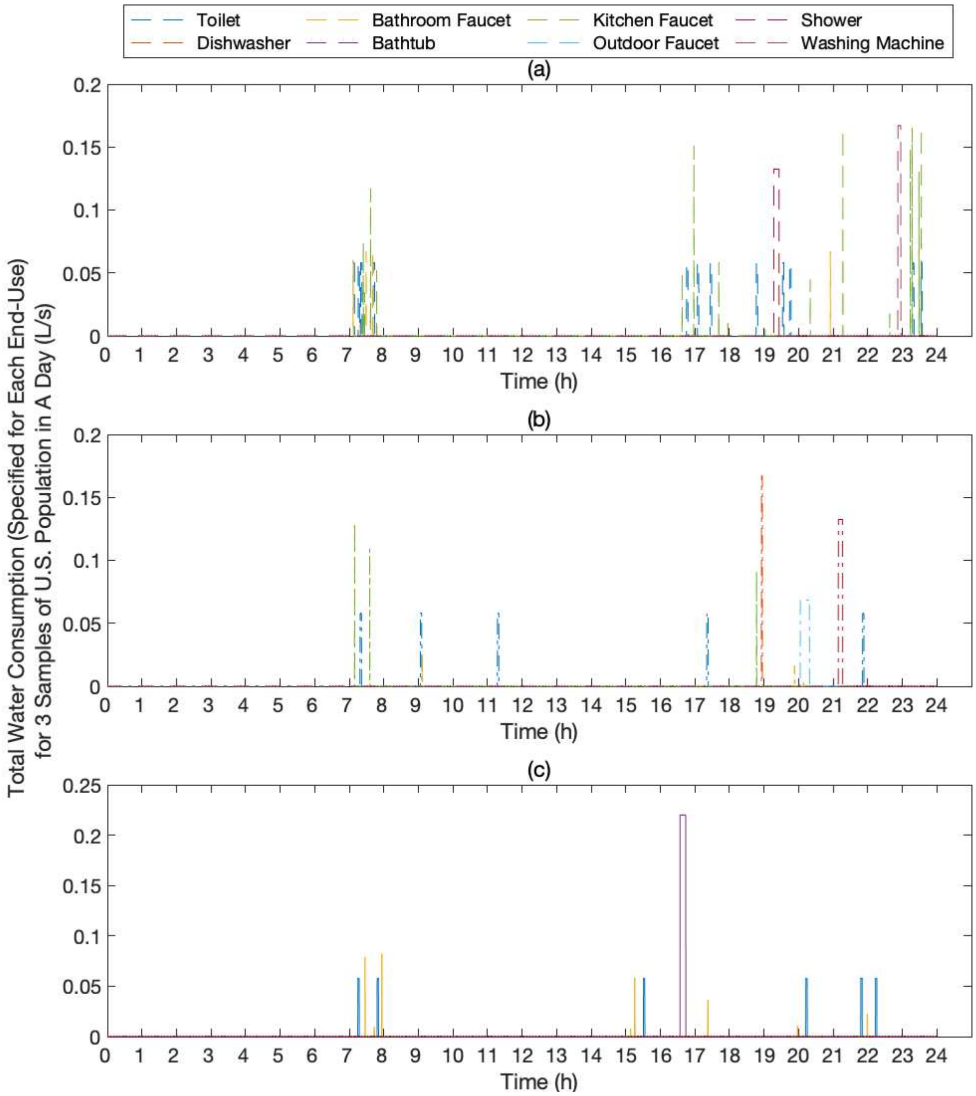

Figure 2.3: An illustration of the total daily water consumption (specified for each end-use) (L/s) for 3 U.S. population samples: (a) a working female, (b) a senior, and (c) a teenager.

11:00 to 17:00, the mid-peak price time is from 7:00 to 11:00 and from 17:00 to 19:00, and the off-peak price time is from 19:00 to 7:00. The electricity prices for the three periods are 17.0, 11.3, and 8.2 $¢/kWh$, respectively. Even though nowadays, price plans and rates for electricity can vary widely, ToU pricing is indeed a growing trend globally, and many regions are transitioning toward more dynamic and flexible pricing structures. This trend aligns with efforts to modernize power systems, enhance grid resilience, and promote sustainability. Advanced metering infrastructure (AMI) and digital technologies enable more granular control over pricing, facilitating the implementation of ToU rates. Consumers,

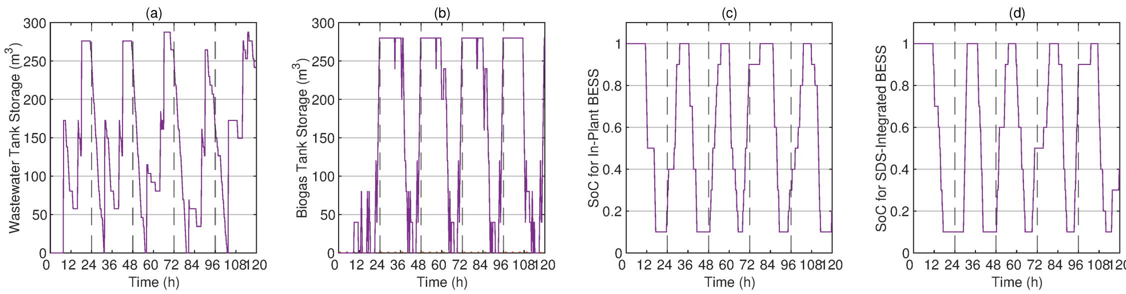

Figure 2.4: The changes in storage capacity for (a) the wastewater tank, (b) and the biogas tank; The SoC profiles for (c) the in-plant BESS, and (d) the BESS integrated into the SDS.

businesses, and utilities are increasingly recognizing the benefits of ToU pricing in terms of cost savings, sustainability, and improved grid management.

2.4.2 Simulation Results and Analysis

The changes in the wastewater tank, biogas tank, in-plant BESS, and SDS-Integrate BESS during the five-day energy management process are detailed in Fig. 2.4. Specifically, the change in the wastewater tank is shown in Fig. 2.4 (a). Due to the vast water usage peak in the morning, which is almost aligned with the electricity consumption morning peak, the wastewater tank temporarily collects the wastewater and waits for later treatment to meet the needs of grid voltage quality after interacting with the DSO. Then, since the electricity price is still at its lower level, to minimize the electricity cost, as long as informed by the DSO that the first possible peak load is overcome, the mid-peak price is immediately used to empty a little bit of the previously accumulated wastewater, treated along with the real-time incoming wastewater. This also prepares for the upcoming on-peak electricity price period starting at 11:00. During peak electricity price periods, more incoming wastewater will be stored. However, since there is another peak in water use around midnight, although the electricity price is high, some wastewater is released from the wastewater tank to free up space for peak water consumption and electricity usage in the evening. For the biogas tank, as shown in Fig. 2.4 (b), to minimize the power purchased from the grid during the on-peak price period, the biogas tank is prepared at a very early stage. For example, the

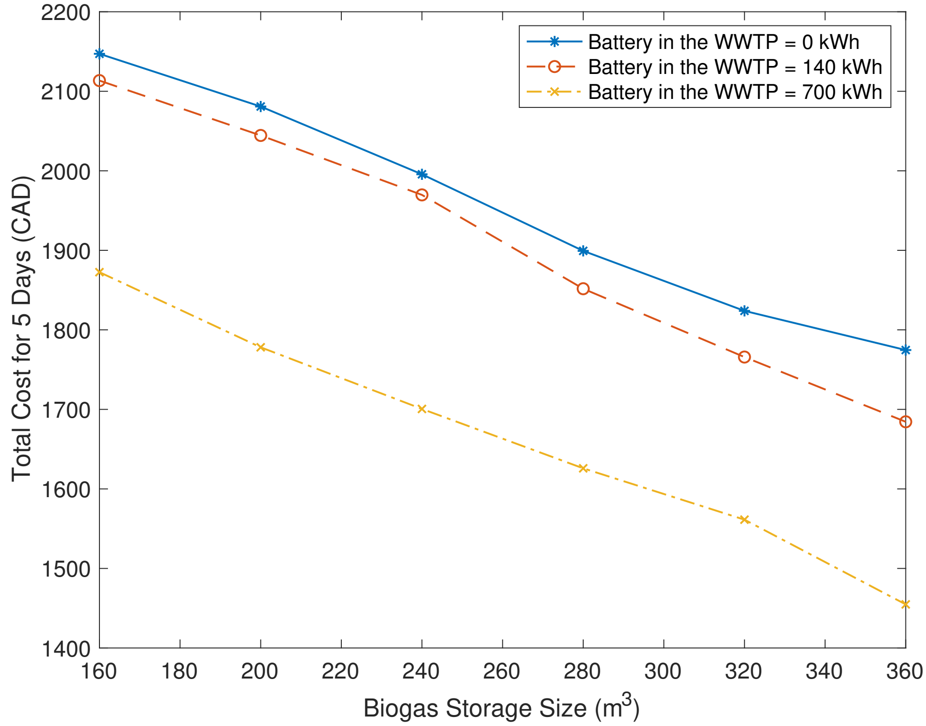

Figure 2.5: Results of cumulative cost over the five-day energy management process with respect to different capacities of in-plant BESS.

biogas tank continues storing biogas as soon as the first period with voltage issue caused by the overlapping of the morning electricity and water usage peaks has passed. And the biogas is released at on-peak price periods to generate more energy to reduce external electricity usage during that period. During the second mid-peak price period (17:00-19:00), the biogas in the tank oscillates. Through interaction with the SDS, the peak electricity consumption in the evening can be overcome. This can increase the minimum system voltage at an acceptable cost to help maintain system voltage quality by pre-depositing and releasing biogas on time. For both the in-plant and independent BESS, they store electricity when the price is low, and discharge as much as possible when the price becomes high, so as to maximize both agents' revenue from selling power. Also, better voltage quality can be achieved by benefiting from the interactions between the sustainable WWTP and the BESS in the SDS. For example, the SoC profiles of these BESSs are differentiated from each other, which can help avoid concentrated power injections and drawings.

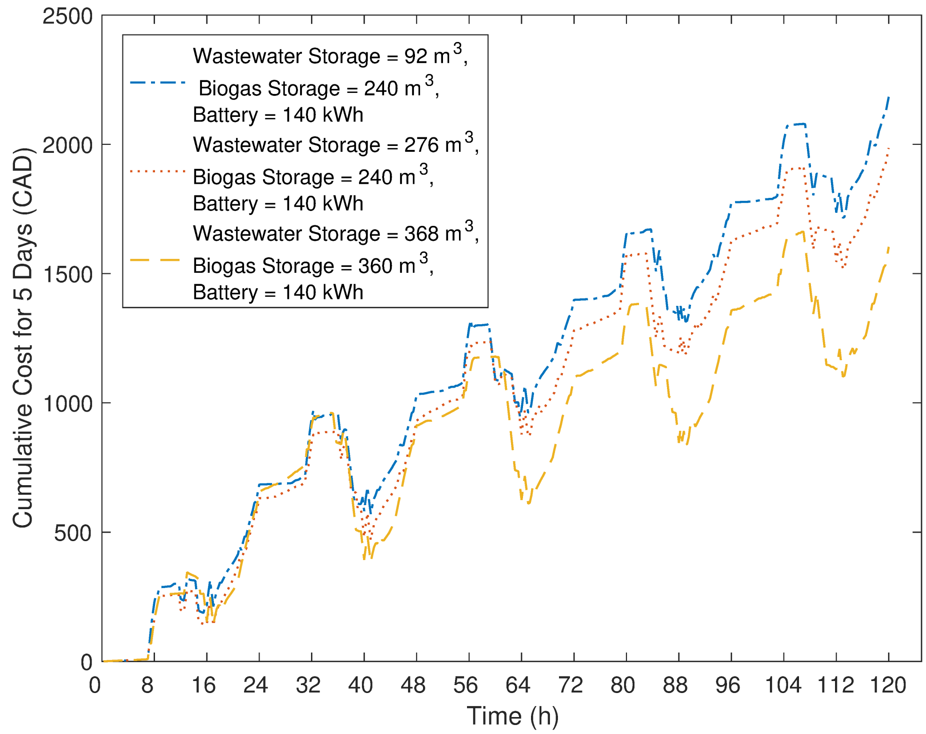

Figure 2.6: Results of cumulative cost over the five-day energy management process with respect to different capacities of wastewater and biogas storage devices.

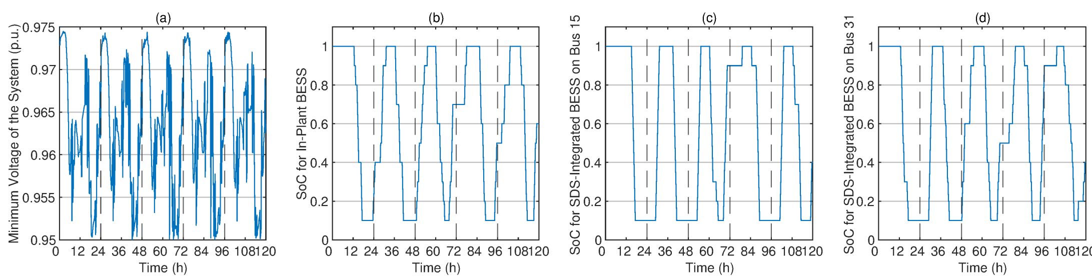

Figure 2.7: Results of integrating an additional BESS into the SDS: (a) Overall system minimum voltage profile; The SoC profile for (b) the in-plant BESS, (c) the BESS integrated into the SDS at bus 15, and (d) the BESS integrated into the SDS at bus 31.

Furthermore, we analyze the impact of different parameters of RES in the sustainable WWTP on the electricity cost. The results are shown in Fig. 2.5. As the size of the biogas tank increases, the cost decreases. Similar results are also applied to the in-plant BESSs. It can be concluded that larger storage devices allow for better control of the system, resulting in lower electricity costs. Also, Fig. 2.6 highlights the variation in electricity cost with respect to the changes in the size of the wastewater and biogas tanks. It demonstrates that larger storage of either tank can effectively reduce the cost. In addition, we add one more

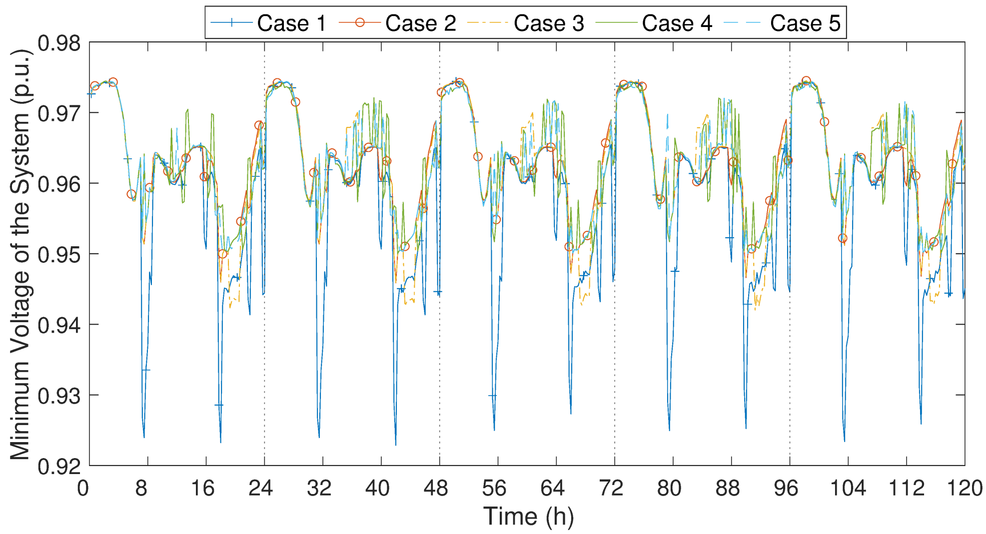

Figure 2.8: Overall system minimum voltage profile in all cases.

SDS-integrated BESS at bus 15 in the SDS to analyze its impact on energy management. The results are shown in Fig. 2.7. We can see that the two BESSs operate differently in terms of charging/discharging. These offsets from this difference can improve the system voltage profile.

2.4.3 Comparative Studies

To further validate the performance of the proposed stochastic energy management of sustainable WWTPs considering interactions with SDSs, the following cases are considered:

- Case 1: Baseline case with optimal energy management of traditional WWTPs [44, 50];
- Case 2: Method in [48], where sustainable WWTPs are considered, while RES are not optimally controlled;
- Case 3: Methods in [64, 65], optimal energy management of sustainable WWTPs;
- Case 4: The proposed method, with optimal energy management of sustainable WWTPs considering interactions with SDSs;
- Case 5: The proposed method with pruning algorithm.

Table 2.1: COMPARISON RESULTS OF DIFFERENT CASES

Case	1	2	3	4	5
Electricity Cost (CAD $)	12951.18	4109.93	2905.70	1851.72	2330.08
Computational time (Hr)	0	0	0.07	9.32	3.91

Fig. 2.8 shows the overall minimum voltage of the SDS during the five-day energy management process. In Case 1, we can see the voltage level is far less than the lower bound of the voltage limitation, i.e., 0.95 p.u., especially at peaks water use. The reason is that the load of WWTP is very heavy without the supplemental power supply from renewable energy. In comparison, by installing the uncontrolled RES, the voltage drops can be avoided in Case 2. However, since no optimal energy management is imposed on the RES in the sustainable WWTP, the utilization of renewable energy could not be optimized. Moreover, Case 3 optimally controls the RES to increase the efficiency of the sustainable WWTP, thus the power consumption is reduced and the impact of WWTP on the voltages of SDS is alleviated. However, since the interactions between the sustainable WWTP and SDS are not considered in Cases 1, 2, and 3, the requirement of voltage limitation cannot be fully satisfied, especially during the peak load periods. By contrast, in Case 4, the voltages are within the limitation throughout the horizon. This is a benefit from the stochastic energy management of sustainable WWTP and considering interactions with SDS. In other words, the multi-agent interactions implemented via I-POMDPs can achieve the best voltage regulation performance. Also, we can see Case 5, using the proposed pruning algorithm, can achieve comparable results in voltage regulation with Case 4, even with a reduced computational complexity. Moreover, Table 2.1 shows the electricity cost of WWTPs over the five-day energy management process. We can see that the proposed method can achieve the lowest electricity cost of $1851.72, compared with other methods, especially the highest electricity cost of $12951.18 obtained by Case 1, considered the most commonly used WWTP in the industry. It demonstrates the necessity of incorporating RES in sustainable WWTPs, coordinating RES with wastewater treatment processes, and interacting with

SDSs. Another feature observed is that consideration of the stochastic energy management of sustainable WWTPs interacting with SDSs may impose a computational burden. To this end, by applying the proposed pruning algorithm, the computational time is reduced significantly. Note that the optimal policy can be derived monthly in advance to minimize the impact of weather fluctuations, hence, such a computational time does not affect the sustainable WWTP operation.

2.5 Summary

In this chapter, a multi-agent stochastic energy management scheme is proposed for sustainable WWTPs considering interactions with SDSs. The problem is formulated as an I-POMDP to address the randomness of wastewater flow, light intensity, and load demand, as well as the multi-agent coordination between the sustainable WWTP, DSO, and BESSs. An exact solution based on α-vectors is derived to determine the optimal WWTP operation policy. Also, a pruning algorithm based on electricity price analysis is proposed to increase the computational efficiency. Moreover, the proposed energy management scheme is performed on the IEEE 33-Bus Test Feeder. The simulation results demonstrate that the stochastic energy management of the sustainable WWTP considering interactions with SDS can significantly reduce the electricity cost. Also, the multi-agent coordination between sustainable WWTP, DSO, and BESSs implemented through I-POMDPs can achieve a better voltage regulation performance, then a more stable system. In addition, the proposed pruning algorithm can achieve comparable results to the exact scheme with significantly reduced computational time. This also reminds us that in the urbanization process, overlooked major energy consumers have the potential to support the system and may even become net energy providers under specific conditions. Instead of allocating large investments towards upgrading PDS assets, it would be more advisable to explore alternative, cost-effective solutions, such as sustainable WWTPs, to address the challenges faced by the system.

Chapter 3

Multi-Timescale Stochastic Electrical and Thermal Energy Management for Sustainable Communities with Wastewater Treatment Plants

Building on the previous chapter, this chapter delves into the stochastic energy management of sustainable communities connected to smart distribution systems. The sustainable community we propose integrates multiple RES, diverse energy storage devices, an innovative wastewater treatment plant, and a neighboring smart building. Considering the variability in electric load, wastewater flow, RES, and weather conditions, this optimal energy management problem is formulated based on the multi-timescale Markov decision process. The objective is to minimize the total operating cost of the community while mitigating the adverse impacts on the SDS. To evaluate the effectiveness of the proposed energy management scheme, we assess its performance using the IEEE 33-Bus Test Feeder, authentic weather data, and modeling of PV and hydropower generation, wastewater flow rate and processing.

As mentioned in previous sections, fortunately, there is also a vast but so far unnoticed renewable energy potential in the sector. Besides generating electricity from the micro-hydropower system, and CHP units, recent research works indicate that there are three possible places for waste heat recovery from sewage [19], and for consumption points near WWTPs, heat supply from the effluent is considered more advantageous than heat extraction in sewers. On this basis, for a WWTP, the heat energy provided by combining the CHP system, and the heat recovery system as heat sources is very considerable. At the same time, in order to maximize economic benefits, due to the characteristics of thermal energy, it is not suitable for long-distance transmission. Waste heat can be utilized in agriculture, forestry, or for low-temperature heating needs in settlements [22]. Therefore, in this chapter, the novel WWTP, along with nearby smart buildings and other RES, as well as energy storage devices, form a sustainable community to maximize the utilization of both electrical and thermal energy. Energy will flow within the proposed sustainable community and the connected SDS.

In this chapter, a comprehensive mathematical model is developed for the proposed sustainable community within the SDS. The model incorporates various components such as PV systems, CHP units, hydroelectric generating sets, heat recovery systems, thermal energy storage, and battery energy storage, connecting to the smart distribution system. Additionally, an energy management problem is formulated, integrating models across domains, to maintain the voltage quality of the SDS while minimizing energy costs of the sustainable community encompassing the adjacent building and the innovative WWTP. The MMDP is used to formulate this optimal energy management problem, with different timescales employed for modeling wastewater, electrical, and thermal processes. And the backward induction method is employed on value iteration to obtain the solution.

3.1 System Model

In this section, to avoid repetition, the thermal-related models are presented, providing a supplementary contribution to the previous Chapter 2. Establishing the sustainable community including PV generation, the advanced WWTP, the proximate building, and electrical and thermal energy storage systems, connected to the SDS. The system structure is shown in Fig. 3.1.

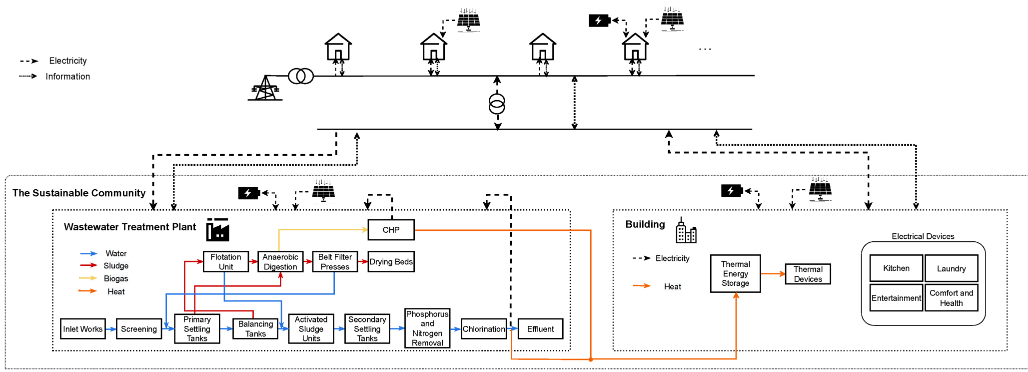

Figure 3.1: The architecture of the sustainable community.

3.1.1 Modeling of Wastewater Heat Recovery

In addition to the CHP, another source of thermal energy resides in the recovery of waste heat from sewage in the plant, which can be expressed as

$$q_t^{hr} = (\mathcal{T}_{ifl} - \mathcal{T}_{ofl}) \cdot S_t \cdot \zeta, \tag{3.1}$$

where the temperature difference represents the cooling of the sewage and ζ indicates the specific heat capacity of water.

The total heat extracted from the sustainable WWTP is a combination of the heat generated from the produced biogas and the heat recovered from the effluent.

3.1.2 Modeling of Temperature-Dependent Thermal Load in the Hybrid Microgrid

Based on [108] and [109], the interior temperature for each time slot could be simplified to

$$T_{t+1}^i = T_t^i e^{(-\Delta t/(R_{th}\xi))} + (R_{th} q_t^{ti} + T_t^o)(1 - e^{(-\Delta t/(R_{th}\xi))}), \tag{3.2}$$

where T_t^i and T_t^o represent the indoor and outdoor temperatures at any time t, respectively. Meanwhile, Δt indicates the time interval, R_{th} is the thermal resistance of the shell, which is determined by the thermal conductivity and material thickness, ξ is the specific heat ratio of air, and q_t^{ti} shows the total input thermal energy for any time slot t. Specifically, in this sustainable community, q_t^{ti} equals the combination of total thermal energy extracted from the wastewater, the heat available from thermal storage, and the thermal energy produced by purchasing additional electricity.

3.1.3 Thermal Energy Storage Model

The modeling of the thermal energy storage relies on injected ($q_t^{ht} > 0$) or extracted ($q_t^{ht} < 0$) thermal power, depending on

$$s_{t+\Delta t}^{ht} - s_t^{ht} = q_t^{ht}\Delta t, \tag{3.3}$$

where s^{ht} indicates the available thermal energy stored in the device and q_t^{ht} is the thermal power change of the heat storage device between any time t and $t + \Delta t$.

3.1.4 Modeling of Stochastic Weather Conditions

The stochastic weather conditions of temperature and light intensity are modelled by the non-homogeneous Markov chain. A day can also be divided into several parts by using the segmentation method. Each part has the same uniform state transition probability. For different parts, they have different non-homogeneous state transition probabilities. Based on the Markov chain model, the state transition probability for outside temperature $Pr(T_{t+1}^o|T_t^o)$ and light intensity $Pr(L_{t+1}^{pv}|L_t^{pv})$ can be derived [98].

3.2 Formulation of the Stochastic Energy Management Problem

To formulate the energy management problem for this proposed sustainable community, considering the interactions with the smart distribution system, we use a multi-timescale Markov decision process. This energy management model incorporates multiple timescales, in comparison with the traditional Markov decision process. This is because the temperature usually takes some time to change, causing thermal loads to change slowly; the electrical load, however, changes much faster. At the same time, water usage, like electricity, changes rapidly, because most high-frequency water usage is short-lived. And in WWTPs, sewage treatment is closely related to energy consumption, as well as production capacity, allowing it to be modelled also as a fast MDP. Furthermore, unlike conventional multi-timescale MDPs, the dual-timescale MDP here is two interacting parallel processes due to the close connection of electrical, wastewater, and thermal processes.

3.2.1 Thermal Process on Slow Timescale

A slow timescale (STS) MDP is utilized to model the thermal process, as heat exchange, heat transport, and CHP ramping occur relatively slowly and result in gradual changes. The discrete time slots are evenly distributed by the duration Δt^s. This STS thermal process can be prescribed as a single time-scale MDP which has a finite state space ($\mathbb{S}^s$) and a finite action space ($\mathbb{A}^s$), while at any time s in STS MDP, they are:

- $S_s^s =< T_s^i, T_s^o, s_s^{ht} >$, where $S_s^s \in \mathbb{S}^s$
- $A_s^s =< q_s^{chp}, q_s^{hr}, q_s^e, q_s^{ht} >$, where $A_s^s \in \mathbb{A}^s$

where at each time s, the two T terms represent the indoor and outdoor temperature, s_s^{ht} shows the status of the thermal storage. At the same time, for action space, q_s^{chp} and q_s^{hr} are actions related to the thermal process taken by the sustainable WWTP, q_s^e and q_s^{ht} are actions taken by the housing sector. And by definition, states and actions remain constant at each time step in this thermal scale Markov decision process.

Then, the Markov decision process non-homogeneous state transition function for the slow timescale can be calculated as

$$Pr_s^s(S_{s+1}^s | S_s^s, A_s^s) = \begin{cases} Pr_s(T_{s+1}^o | T_s^o), & \text{if (3.2) and (3.3) hold} \\ 0, & \text{otherwise.} \end{cases} \tag{3.4}$$

And at any moment s, when the state is S_s^s, by taking action A_s^s, the process will immediately receive a reward R_s^s, in this case, the cost of heating purposes.

Considering the comfort of the indoor environment, the limitation of the thermal energy generator, as well as the thermal energy storage, for any $s \geq 0$, the following constraints should be satisfied:

$$T^i_{min} \leq T^i_s \leq T^i_{max}, \tag{3.5}$$

$$q^{chp}_{s-1} - q^{chp}_{ramp}\Delta t^s \leq q^{chp}_s \leq q^{chp}_{s-1} + q^{chp}_{ramp}\Delta t^s, \tag{3.6}$$

$$B^l(q^{ht}) \leq q^{ht}_s \leq B^u(q^{ht}), \tag{3.7}$$

$$B^l(s^{ht}) \leq s^{ht}_s \leq B^u(s^{ht}). \tag{3.8}$$

3.2.2 Wastewater and Electrical Process on Fast Timescale

Analogously, the time axis for the fast timescale (FTS) MDP is divided into consecutive time slots of equal duration Δt^f and satisfied with $n\Delta t^f = \Delta t^s$. Assign the finite state space ($\mathbb{S}^f$) and the action space ($\mathbb{A}^f$) at any time t in FTS MDP as follows:

- $S^f_t =< \psi_t, s^b_t, T^i_t, L^{pv}_t, p^{grid}_t, s^{ww}_t >$, where $S^f_t \in \mathbb{S}^f$
- $A^f_t =< p^{sell}_t, p^{buy}_t, p^{chp}_t, \omega_t >$, where $A^f_t \in \mathbb{A}^f$

where s terms represent the components stored in BESSs and the wastewater flow rate, which corresponds to how much energy is required for treatment and how much energy can be recovered during processes, while p^{grid}_t represents the status of the grid. Moreover, for batteries, ψ_t represents the set of health and ω_t indicates the depth of charging/discharging. For the action spaces, p^{sell}_t and p^{buy}_t are the power injected/drawn from the grid in each time slot t. The last p item denotes the action related to the CHP.

Meanwhile, the state transition function of this water and electrical related MDP can be calculated as

$$\begin{aligned} Pr^f_t(S^f_{t+1}|S^f_t, A^f_t, S^s_s, A^s_s) =& Pr(L^{pv}_{t+1}|L^{pv}_t)Pr(p^{grid}_{t+1}|p^{grid}_t)Pr(s^{ww}_{t+1}|s^{ww}_t) \\ & Pr(s^b_{t+1}, \psi_{t+1}|s^b_t, \psi_t, \omega_t). \end{aligned} \tag{3.9}$$

Then the corresponding immediate cost function R^f_t of this FTS MDP can be expressed as

$$R^f_t(S^f_t, A^f_t, A^s_s) = C^{bat}(s^b_t, \psi_t, \omega_t) + C^{ele}, \tag{3.10}$$

where the C^{bat} is the cost of degradation of all batteries and the C^{ele} indicates the total cost of power consumption for the system, which can be calculated as

$$C^{ele} = r_t \mathcal{D}(p_t^{com} - p_t^b - p_t^{pv} - p_t^{chp} - p_t^{hy}), \tag{3.11}$$

where the community load p_t^{com} contains the load of the WWTP and other residences in the district. Meanwhile, r_t is the price of electricity at any time t, and $\mathcal{D}$ is the duration.

For all slots t within STS MDP slot s, constraints for the FTS MDP are:

$$B^l(SoC) \leq s_t \leq B^u(SoC), \tag{3.12}$$

$$0 \leq |\lambda_t^{bat}| \leq 1, \tag{3.13}$$

$$-|\bar{I}^c| \leq p_t^{bat}/U \leq |\bar{I}^{disc}|, \tag{3.14}$$

$$B^l(s^w) \leq s_t^{ww} \leq B^u(s^w), \tag{3.15}$$

$$B^l(q_s^{chp}) \leq p_t^{chp} \leq B^u(q_s^{chp}), \tag{3.16}$$

$$B^l(V^{bus}) \leq V_t^{bus} \leq B^u(V^{bus}), \tag{3.17}$$

$$B^l(P^{bus}) \leq P_t^{bus} \leq B^u(P^{bus}), \tag{3.18}$$

$$B^l(Q^{bus}) \leq Q_t^{bus} \leq B^u(Q^{bus}), \tag{3.19}$$

$$T_{min}^i \leq T_t^i \leq T_{max}^i. \tag{3.20}$$

Among them, the first three equations are the constraints for the battery, which are mainly the SoC, changes for the SoC, and the current. At the same time, equation (3.16) is the constraint of CHP electric power at a specific thermal power output in the following thermal load mode. Considering the stability of the smart distribution system, equations (3.17)-(3.19) should be satisfied. Furthermore, preserving a livable environment remains essential.

3.3 Solution of the Stochastic Energy Management Problem

According to the concept of MMDP, when each thermal process period ends, the overall reward includes the reward of the thermal process in this time step ($R_s^s(A_s^s)$) and the rewards of n water and electrical processes in the same period. Therefore, by coupling all FTS MDP iterations that occur within a single STS MDP time slot, the induced reward function R can be expressed as

$$R_s(S_s^s, A_s^s, S^f, \pi_{sn}^f) = R_s^s(A_s^s) + \mathbf{E}[\sum_{t_{sn}}^{t_{(s+1)n-1}} R_t^f(S_t^f, A_t^f, A_s^s)|S_{t_{sn}}^f = S^f], \tag{3.21}$$

where the second term of the equation represents the expected value of the sum of n time steps FTS Markov decision process. Here, S^f indicates the initial state of the n-slot FTS MDP, and π_{sn}^f is the collection of all policies for slots in the FTS from time t_{sn} to $t_{(s+1)n-1}$. The non-homogeneous policy for this thermal process can then be defined as π_s^s, and $\pi_s^s(S_{t_{sn}}^f, S_s^s) = A_s^s$.

After that, in the case of a stable system, the value function for this finite stochastic multi-timescale energy management problem with the objective of minimizing the total cost during the assigned time horizon can be expressed as

$$V = \min_{A_s^s \in \mathbb{A}_s^s, A_t^f \in \mathbb{A}_t^f} \{\sum_s [R_s^s(A_s^s) + \mathbf{E} \sum_{t_{sn}}^{t_{(s+1)n-1}} R_t^f(S_t^f, A_t^f, A_s^s)]|S_{s_0}^s = S^s, S_{t_0}^f = S^f\}. \tag{3.22}$$

At the same time, constraints of heat, water and electricity processes need to be met.

For this energy management problem, the solution is the optimal policy for both processes for each period within the specific time frame. Since the value function of the starting point is the reward-to-go function of a finite Markov decision process, we could then rewrite equation (3.21) as

$$R_s(S_s^s, A_s^s, S_{t_{sn}}^f, \pi_{sn}^f) = R_s^s(A_s^s) + V_{t_{sn}}^{\pi_{sn}^f}, \tag{3.23}$$

where the $V_{t_{sn}}^{\pi_{sn}^f}$ denotes the s-th n horizon MDP reward for the water and electricity process. Accordingly, the multi-timescale Markov decision process in the finite time domain has the corresponding Bellman equation:

$$V_s^* = \min_{A_s^s \in \mathbb{A}_s^s, A_t^f \in \mathbb{A}_t^f} \{R_s^s(A_s^s) + V_{tsn}^{\pi_{sn}^f} + \sum_{S_{s+1}^s \in \mathbb{S}^s} \sum_{S_{t_{(s+1)n}}^f \in \mathbb{S}^f} [Pr_s^s(S_{s+1}^s | S_s^s, A_s^s) Pr_s^{fs}(S_{t_{(s+1)n}}^f | S_s^s, A_s^s, S_{t_{sn}}^f, \pi_{sn}^f) V_{s+1}^*]\}, \tag{3.24}$$

where the $Pr_s^{fs}(S_{t_{(s+1)n}}^f | S_s^s, A_s^s, S_{t_{sn}}^f, \pi_{sn}^f)$ indicates the initial transition function for n Markov decision processes for wastewater and electrical processes.

The timescale for this model can be adjusted by the local electricity price plan and rates, wastewater flows, and battery parameters, depending on the accuracy of the weather forecasting and the computational complexity. Once the timescales are set, the backward induction method can be used in equation (3.24) to solve this finite horizon multi-timescale Markov decision process [60]. Both timescales could be computed in parallel. And the computational complexity is acceptable for a small grid-connected sustainable community.

3.4 Case Studies and Discussion

In this case study, power flow data of the IEEE 33-Bus Test Feeder is used as an example, for which the layout is shown in Fig. 3.2, and the proposed sustainable community is connected to bus 8. The per unit voltage lower and upper limits of each bus are 0.95 p.u. and 1.05 p.u., respectively.

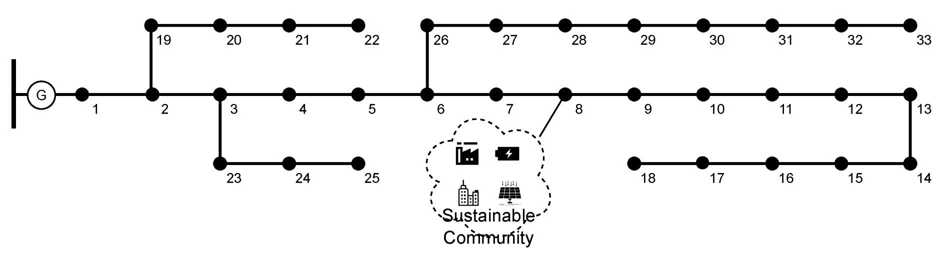

Figure 3.2: An illustration of the IEEE 33-Bus Test Feeder with an integrated sustainable community.

Wastewater flows are generated by the stochastic bottom-up water use model mentioned in Subsection 2.1.1. The household composition of this sustainable community is from the

United Kingdom Census [103]. This study also targets dry weather conditions. Frequency can be modelled with binomial, Poisson, and negative binomial distributions. At the same time, the intensities are mostly fixed, model-specific, or obey uniform distributions. While there are more variations for the duration, we find that they could be modelled as chi-square distributions, log-normal distributions, and fixed or special models. The head of the micro-hydroelectric system varies according to the design of each WWTP, as well as the location of the turbines, where we use a net head equal to 2.8 meters [11] to represent the median case. The Kaplan turbine is selected and installed at the output of the chlorination section, as shown in Fig. 3.1. For timescales, in this case study, we choose Δt^f= 1 minute for the wastewater and electric process. This is due to frequent changes in electricity demand, and the short duration of most residential water use. At the same time, it takes much longer to raise the temperature of a building with heaters. In addition, a certain amount of time is needed for the heat recovered by the sewage treatment plant to be transported inside the innovation community. We define the time slot of the thermal process (Δt^s) as 30 minutes, because according to [109], for a distance of 1.5 km, the transportation time for the recovered waste heat is approximately 30 minutes. Although the lithium-ion battery can be charged to 100% and discharged to 0%, to increase battery life, maintain system voltage quality, and maximize battery utilization, here, we consider the charge and discharge range to be 0.1 to 1, respectively. At the start of the energy management process, we assume the in-plant and in-building BESSs are fully charged, whereas the opposite is true for the heat tank. The electricity rates used here are the Time-of-Use (ToU) prices established by the OEB since November 1, 2021 [107], with the on-peak (11:00 to 17:00), mid-peak (7:00 to 11:00 and 17:00 to 19:00), and off-peak (19:00 to 7:00) prices to be 17.0, 11.3, and 8.2 $¢/kWh$, respectively.

To evaluate the performance of our proposed sustainable community and energy management approach, some cases are considered for comparison:

- Case 1: This is a baseline case where the conventional community has neither renew-

Table 3.1: TOTAL ENERGY COST COMPARISON

Total Cost (CAD)	After 24 Hours (i.e. 1 Day)	After 48 Hours (i.e. 2 Days)	After 72 Hours (i.e. 3 Days)	After 96 Hours (i.e. 4 Days)	After 120 Hours (i.e. 5 Days)
Minimal for Case 1 (T^i = 22 °C)	5926.03	11568.70	17546.55	22642.05	27045.18
Case 2	4086.09	7944.58	12140.92	15608.13	18490.10
Case 3	3529.99	6946.93	10708.42	13893.04	16585.66

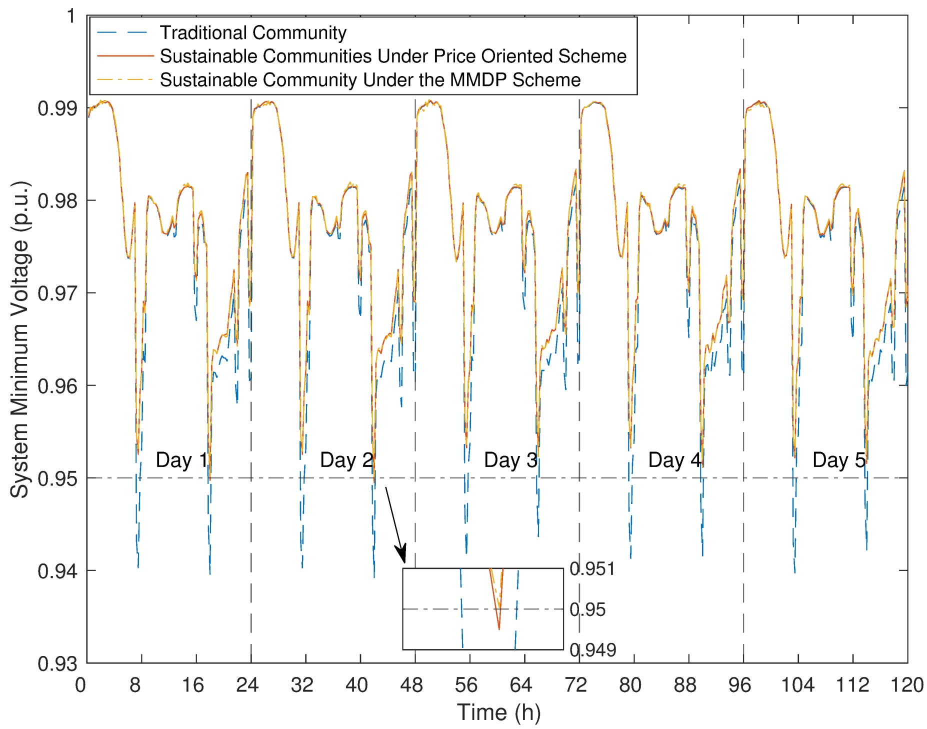

Figure 3.3: Comparison of the lowest voltage of the system.

able energy sources nor optimized control;

- Case 2: Implement comprehensive price-driven controls over the sustainable community;

- Case 3: The sustainable community is governed by using our proposed stochastic approach with the exact solution, formulated as a multi-timescale process.

By building a sustainable community and applying simple controls (Case 2 vs. Case 1), the total cost can be significantly reduced. The electricity consumption for energy supply alone is reduced by 31.17%, while the heating cost is also reduced by 30.95%. However,

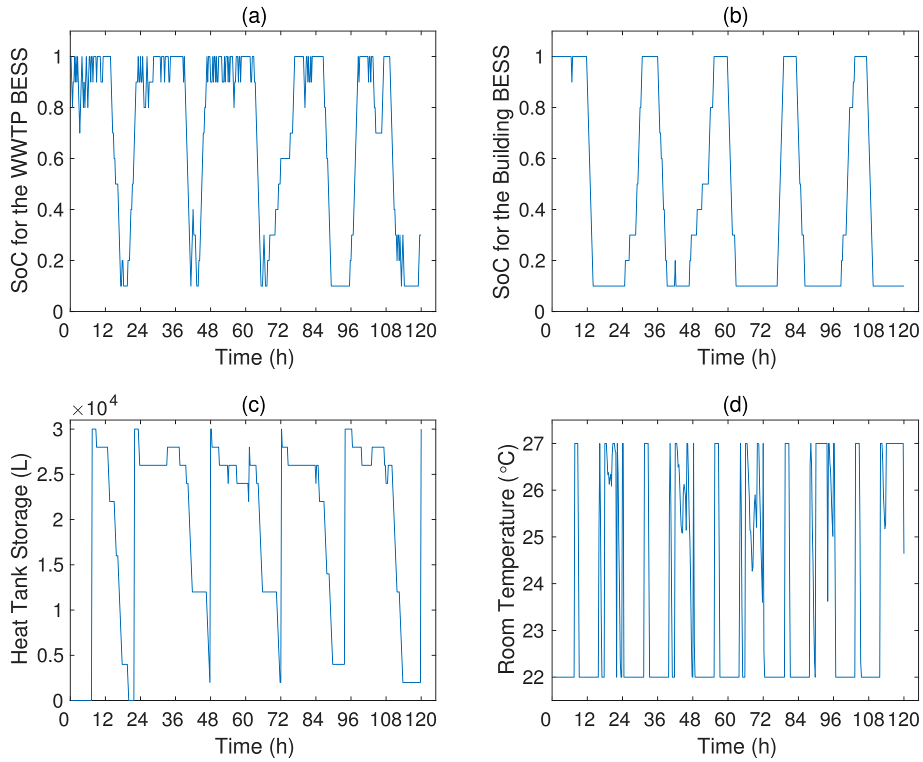

Figure 3.4: Results of this sustainable community under the MMDP scheme: The SoC profiles for (a) the BESS inside the WWTP, (b) the BESS in the building, and (c) the heat tank; (d) Indoor temperature in the residential building.

as shown in Fig. 3.3, without the proper control of them, the system cannot fully meet the grid voltage requirements, especially in the evenings. After adopting our proposed multi-timescale energy management approach, the minimum voltage of the system can be satisfied, thereby improving the voltage quality of the system. And with further savings of more than 10% in total costs (details are in Table 3.1). Moreover, as can be observed from the first two subplots of Fig. 3.4, under the control of MMDP, the SoCs of the in-plant and in-building batteries are not identical to each other. This could also help to avoid concentrated power injections and drawings. With the help of the thermal tank, in conjunction with the sustainable WWTP, the building in this region can maintain indoor temperatures within the comfortable range (22-27°C) at a low cost. The specific room temperature changes during this period in winter are shown in Fig. 3.4 (d).

3.5 Summary

This chapter investigates a stochastic multi-timescale energy management approach for the sustainable community connected to the SDS. An MMDP model is used to formulate this energy management problem, which consists of two coupled timescales, one for thermal processes, and the other for the wastewater and electrical processes. A case study shown in Section 3.4 has proven that the proposed sustainable community and energy management approach can abundantly reduce the total energy cost while ensuring the living conditions of inhabitants and satisfying the system voltage quality requirements. Reduced energy costs come from both power and heating.

Chapter 4

Conclusions and Future Works

Conventional power distribution systems are shifting towards more efficient, reliable, sustainable, and intelligent SDSs to accommodate the ever-increasing load demands and environmental concerns. SDSs use cutting-edge technologies, devices, and controls that communicate and work together to deliver power more reliably and efficiently. The use of two-way communication technologies, control systems, and computer processing enables the “smart grid” technologies. SDSs also benefit consumers by giving them easier access to their own data, which in turn enables them to better manage energy consumption and costs. Utilities benefit from a modernized grid, including improved security, increased system voltage quality, increased integration of renewables, and lower operational costs.

The results of this thesis can serve as a basis for promoting sustainable urban development in SDSs in the future, such as supporting renewable energy initiatives or advocating energy-efficient building codes. In Chapter 2, a multi-agent stochastic energy management scheme is proposed for sustainable WWTPs, taking into account the interactions with SDSs. To account for the stochastic nature of wastewater flow, light intensity, and load demand, as well as the need for multi-agent coordination between the sustainable WWTP, DSO, and BESSs, the problem is formulated as an I-POMDP. A precise solution is developed to generate the optimal operation policy for the WWTP. Additionally, a pruning algorithm that utilizes electricity price analysis is presented to enhance computational efficiency. Then the proposed energy management schemes are executed on the IEEE 33-Bus

Test Feeder. The results of the simulation indicate that: The stochastic energy management of the sustainable WWTP, which takes into account interactions with SDS, can substantially decrease the energy expenses; The multi-agent coordination among sustainable WWTP, DSO, and BESSs, which is implemented through I-POMDPs, can attain better voltage regulation performance and reasonably maintain the overall voltage quality of the system; Additionally, the proposed pruning algorithm can produce results that are comparable to the exact method while effectively reducing the computational complexity. This inspires us that in the process of urbanization, many neglected major energy consumers have the potential to provide support for the system in one way or another and even become net energy providers under certain conditions. Rather than allocating a substantial investment to upgrade distribution system assets, alternative, cost-effective solutions, such as sustainable WWTPs, should be explored to tackle the challenges faced by the system. Chapter 3 delves into an investigation of a stochastic multi-timescale energy management approach for the sustainable community integrated with the SDS. In formulating this energy management problem, an MMDP model is employed, encompassing two coupled timescales, one pertains to thermal processes, while the other addresses wastewater and electrical processes. The case study outlined in Section 3.4 offers evidence that the proposed sustainable community and energy management approach proficiently reduces the overall energy expenditure. Simultaneously, it prioritizes the living conditions of residents and meets the system voltage quality requirements.

4.1 Contributions of Thesis

The main contributions of this thesis are summarized as follows:

- For the energy consumption and production of sustainable WWTPs, a comprehensive mathematical model is established based on the stochastic end-use model. And various RES are incorporated for renewable energy generation and electricity cost saving. This multi-agent stochastic energy management problem of the sustainable

WWTP is formulated and solved through the utilization of an I-POMDP. The coordination among the sustainable WWTP, the DSO, and BESSs is addressed while accounting for uncertainties. To further reduce the computational complexity of the energy management problem, caused by the curse of history and dimensionality, a pruning algorithm is presented. This algorithm prunes in advance based on the electricity prices of off-peak and on-peak loads, resulting in a reduced set of actions and states.

- The optimal energy management problem, which integrates the models of hydraulics, electricity, thermal, chemistry, and bioenergy, is formulated and solved as an MMDP problem to minimize energy costs of the proposed sustainable community encompassing the adjacent smart building and the sustainable WWTP while maintaining the voltage quality of the SDS. The modeling of wastewater (FTS), electrical (FTS), and thermal (STS) processes employs different timescales. And value iteration is performed by backward induction to obtain the exact solution.

4.2 Directions for Future Work

Although this thesis has addressed several critical issues about the stochastic energy management of sustainable WWTPs and sustainable communities in SDSs, there are still many open issues to be investigated. Here are some potential directions for future work:

- Current approaches are model-based methods. In the future, there is potential to extend these methods to learning-based methodologies, such as multi-agent reinforcement learning or multi-timescale reinforcement learning.

- With the continuous development of the control system, in the face of WWTPs with controllable process details like [51], we will consider how to combine them with renewable energy power generation and storage optimization to find a more suitable method for energy management. Specifically, some components/processes in the wastewater treatment process can be further controlled, such as the aeration unit, pumps, and submerged mixers used in different basins of the plant. However, it is important to note that after implementing process controls, the treated effluent quality may be affected. Therefore, we also need to establish constraints for effluent quality, particularly regarding biochemical oxygen demand (BOD) and total Kjeldahl nitrogen (TKN) concentrations. Additionally, these devices themselves, especially the aeration unit and pumps, also have certain limitations.

- From another perspective, in recent years, the occurrence of extreme weather events has been increasing, prompting a need to consider the role that sustainable WWTPs and communities can play in these disasters. For example, the heat generated from biogas or the thermal energy recovered from wastewater can be utilized in smart buildings, residential areas, and even in priority facilities such as hospitals. However, the efficient utilization of this heat in the face of the stochasticity of ice storms and varying heat demands requires further investigation. This consideration is crucial for ensuring the resilience and effectiveness of sustainable WWTPs and communities in the face of extreme weather events. The potential impact of these facilities in disaster resilience and energy management underlines the need for further research and planning to optimize their role in mitigating the effects of extreme weather.

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