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A Stochastic MPC-Based Flexibility Scheduling Strategy for Community Integrated Energy System Considering Multi-Temporal-Spatial-Scale and Inertia Components

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Abstract: The network trend of isolated communities adds urgency to accelerate the deployment of community integrated energy systems (CIES). CIES effectively combines and optimizes multiple energy systems, leveraging their complementarity for efficient utilization and economical energy supply. However, the escalating intricacies of coupling multiple energy sources and the rising system uncertainties both pose challenges to flexibility scheduling of energy supply and demand. Additionally, the potential flexibility of building thermal inertia and pipeline gas linepack in diverse CIES, encompassing residential, commercial, and industrial communities, remains unexplored. To tackle these issues, a stochastic model predictive control (SMPC) based multi-temporal-spatial-scale flexibility scheduling strategy considering multiple uncertainty sources and system inertia components is proposed. First, the optimization model of CIES is formulated to improve operational flexibility and efficiency, resolve energy discrepancies and expand the capacity for renewable energy utilization. Then, the SMPC-based framework embedding an auto-regressive model and scenario generation method are established to make real-time corrections to the day-ahead scheduling stage and offset the prediction errors of uncertainty sources economically. Furthermore, thermal inertia of the aggregated buildings with different envelopes and linepack in gas pipelines are both leveraged to enhance the flexibility and synergy of CIES. Finally, a case study is executed to verify the effectiveness and applicability of the proposed strategy. The simulation results unequivocally demonstrate that this strategy successfully coordinates and harnesses complementary advantages from various energy sources, fostering a balanced energy supply-demand equilibrium across multiple temporal and spatial scales.

Keywords: community integrated energy system; flexibility scheduling; stochastic model predictive control; multi-temporal-spatial-scale; thermal inertia; gas linepack



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1. Introduction

With the gradual depletion of limited fossil fuel resources and the boost in global energy consumption, the whole world is experiencing an unprecedented energy crisis. This situation is exacerbated by additional problems, such as contradiction between energy supply and demand, low integrated energy efficiency, and rising energy prices. As potential solutions, higher shares of wind and photovoltaic (PV) as well as other renewable energy sources (RES) can effectively reconcile differences between supply and demand [1]. However, the output of RES is substantially affected by weather conditions and has significant uncertainty, which requires additional flexibility to ensure consistent functioning of the complete energy system. To build a more robust energy system, less vulnerable to supply disruptions, the concept of a community integrated energy system (CIES) has been proposed to realize synchronization and mutually beneficial aspects of various energy sources.

Significant endeavors have been dedicated to optimizing the operation of CIES. A CIES is commonly positioned at the terminal of energy transmission networks and extensively

employed in different communities, which can organically achieve the interconnection of diverse energy sectors and establish physical connections between various energy forms [2]. Besides, CIES is generally thought to be a promising method to efficiently improve the utilization rate of RES due to its superior operating efficiency [3]. A distributionally robust dispatching strategy of CIES was proposed to procure active energy sharing interaction and effective profit allocation [4]. Based on integrated demand response (IDR), a stochastic robust optimal model of CIES was established to enhance the equilibrium between energy supply and demand at the community level [5]. In [6], a Stackelberg game optimization model considering a carbon trading mechanism and IDR for CIES was developed, and the effect of diverse user aggregator engagement levels on CIES was comprehensively analysed. An innovative algorithm using a recurrent neural network was proposed for CIES energy management control to optimize energy flows [7].

While the aforementioned studies have delved into various challenging issues concerning the optimal operation and scheduling of CIES, several aspects await improvement including, but not limited to, uncertainty management and dynamic characteristic research, which are pertinent to this work's focus.

The multiple sources of uncertainty and limited prediction accuracy raise formidable challenges to the economic and reliable operation of CIES. To tackle these challenges, a novel stochastic-robust scheduling model for optimal participation of prosumers in CIES was proposed by considering uncertainties derived in various energy transactions [8]. Aiming to break the bottleneck of prediction accuracy, a multi-step short-term forecasting framework for a model predictive control (MPC) strategy was introduced and subsequently implemented in a renewable energy community in Austria [9]. A bi-objective optimization for CIES with correlated uncertainties was introduced based on the improved triangle splitting algorithm [10]. The findings of [11] indicate that the existence of multiple uncertainty sources can change the optimal configuration of a scheduled energy system. Flexible and accurate control of the CIES operation requires effectively alleviating the imbalance between energy generation and consumption caused by significant prediction errors, which brings new demand for multi-time-scale adjustment. As discussed in [12], the integration of diverse time-scale scheduling not only facilitates enhanced coordination between global and local energy management, but also proves to be economically optimal compared to the day-ahead (DA) scheduling. To realize flexibility synergy and uncertainty balancing of the integrated multi-energy system, a two-stage stochastic scheduling scheme consisting of a DA stage and a real-time (RT) stage was investigated based on historical system observations and forecasted future uncertainties [13]. The DA scheduling, RT optimal operation, and coordinated frequency control were studied in [14] to increase share of RES generation. A novel real-time coordinated energy control method based on fast Stackelberg equilibrium learning was presented for the effective coordination of a multi-area IES [15]. In the view of the transient characteristics of district heating network (DHN), an ultra-short-term optimization model was established for IES optimal scheduling [16]. Evidently, these studies complement applications of flexibility scheduling strategies with multiple dispatching periods and higher temporal resolution. However, the system flexibility has not been fully exploited due to the negligence of inertial components in the above-mentioned studies.

The slow dynamic characteristics of DHNs and natural gas systems (NGS) can contribute to the inherent inertia of IES. The inertia is mainly known as the thermal inertia of buildings and the linepack stored in natural gas pipelines. Building energy consumption accounts for more than 70% of electricity usage, which has substantial impacts on system operation [17]. In this regard, building thermal inertia may have the favorable potential to improve the temporal and spatial flexibility of system scheduling. Thanks to the building thermal inertia, the indoor temperature kept within reasonable ranges. In this case, building energy consumption is flexible and can be adjusted according to the system demand with little impact on users' comfort [18]. Many studies have been devoted to the utilization of building thermal inertia. A holistic assessment method was proposed to control the thermal inertia of the building envelope components [19]. In order to improve the oper-

ational flexibility of IES, a novel optimal scheduling model based on chance-constrained programming was proposed while considering thermal inertia of buildings [20]. By using the thermal inertia of the DHN, the peak thermal load can be promptly shifted to the low-valley period, which effectively improves the peak shaving capability of IES [21]. The incorporation of building thermal inertia and thermal comfort requirement for occupants is equivalent to boosting the heat storage capacity of DHN, which positively affects the large-scale and high-proportion utilization of RES. In [22], a DA optimal scheduling model for IES was constructed to reduce the energy storage dependency, which comprehensively considered the thermal inertia, user comfort, and multiple uncertainties. These works have evaluated the superiority of building thermal inertia for DHN operation from different perspectives. However, the specific impact of thermal inertia on the energy consumption of typical buildings within heterogeneous communities has yet to be investigated, and the linepack stored in NGS has not been jointly analysed.

In view of the slow dynamics of NGS, various studies have proposed innovative control and scheduling methods for enhancing the system operation performance through gas linepack flexibility. The linepack flexibility is attributed to the compressibility of natural gas and the slow transmission speed of the dynamic gas flow [23]. In [24], an integrated unit commitment and natural gas network operational problem were studied and the effectiveness of gas linepack on the operation of power distribution network (PDN) was evaluated. Four mixed-integer linear programming (MILP) models were proposed to produce the optimal gas linepack management schemes under various scenarios [25]. By integrating power to gas (P2G) technology with the NGS, it is practical to leverage the inherent linepack flexibility of the IES, and transfer partial electricity variability onto the NGS [26]. A bi-level stochastic market-clearing mechanism was established to evaluate the positive impact of gas linepack on the local level IES [27].

Based on the above research, the operational flexibility, reliability and economy of multi-energy system can be further ameliorated. However, the joint consideration of dynamic characteristics of DHN and NGS is discarded in these studies. Discarding this makes it impossible to provide a precise and efficient control method for the optimal operation of CIES. Simultaneously, existing solutions cannot accurately adapt to RT changes and requirements in renewable generation due to high penetration levels of intermittent RES [28]. Thus, it comes naturally to address propagating uncertainty and variability of RES by supporting real-time quantification of building thermal inertia and gas linepack. One promising method to reach this objective is the stochastic model predictive control (SMPC) strategy, which has numerous viable applications on the optimal control of IES [29]. SMPC is a control technique that uses a predictive model of a system and optimization algorithms to manage prediction errors more effectively and generate control actions that optimize a given objective over a finite time horizon [30]. In the context of IES, SMPC can be used to optimize the operation of multiple energy sources and loads, considering uncertainties in energy supply and demand [31]. Along this pathway, the RT corrective regulation considering system inertial components will be feasible to maintain the stable and efficient operation against all possible realizations of multiple uncertainty sources.

With the continuous evolution of various energy technologies, the evolving energy landscape will be steered towards a common goal, paving the way for CIES. This paper's primary contribution lies in presenting a novel mathematical framework that systematically addresses the identified research gaps in a structured and principled manner, thereby enhancing system flexibility and economic efficiency. The SMPC-based multi-temporal-spatial-scale flexibility scheduling framework couples complicated energy systems, system dynamics that include the building thermal inertia and gas linepack. To elaborate, the originality and main contributions of this study are as follows:

- An SMPC-based multi-temporal-spatial-scale flexibility scheduling strategy is proposed to coordinate different energy sectors and exploit aggregate potential of system flexibility. Various energy forms, diversified energy facilities and multiple scheduling

scales are organically coordinated, which lay the foundation for the more flexible and intelligent synergistic optimization of CIES.

- The SMPC-based framework couples system dynamics, multiple uncertainty sources and day-ahead scheduling results. Analytically, an auto-regressive model is adopted to predict the future information of multiple uncertainty sources and the stochasticity of SMPC strategy is illustrated by using the scenario generation method. Concisely, both scheduling period and prediction horizon are considered in an uncertain environment. In addition, the penalty for deviation from pre-scheduled values obtained by day-ahead scheduling is considered to minimize the entire operation cost.
- The specific impact of thermal inertia on the energy consumption of typical buildings within heterogeneous communities and the buffering effect of gas linepack are thoroughly investigated and evaluated. The cost-saving potential of system inertia components is estimated to assess the performance of the proposed strategy.

The remainder of this paper is organized as follows: (i) Section 2 of the paper presents mathematical model formulations for the CIES, (ii) the framework of SMPC based multi-temporal-spatial-scale flexibility scheduling strategy and the optimization problem are presented in Section 3, (iii) Section 4 revolves around the case studies and numerical simulations, and (iv) ultimately, the overall conclusions are drawn in Section 5.

2. Modelling Method of CIES

This paper focuses on a nearly zero-energy coastal urban district with multiple communities and high penetration rate of RES, and its schematic structure is sketched in Figure 1. The generation of wind onshore, offshore, and solar PV is considered to realize higher shares of RES. The district is composed of three main social functional areas (residential, commercial, and industrial communities), which have energy demand for different purposes.

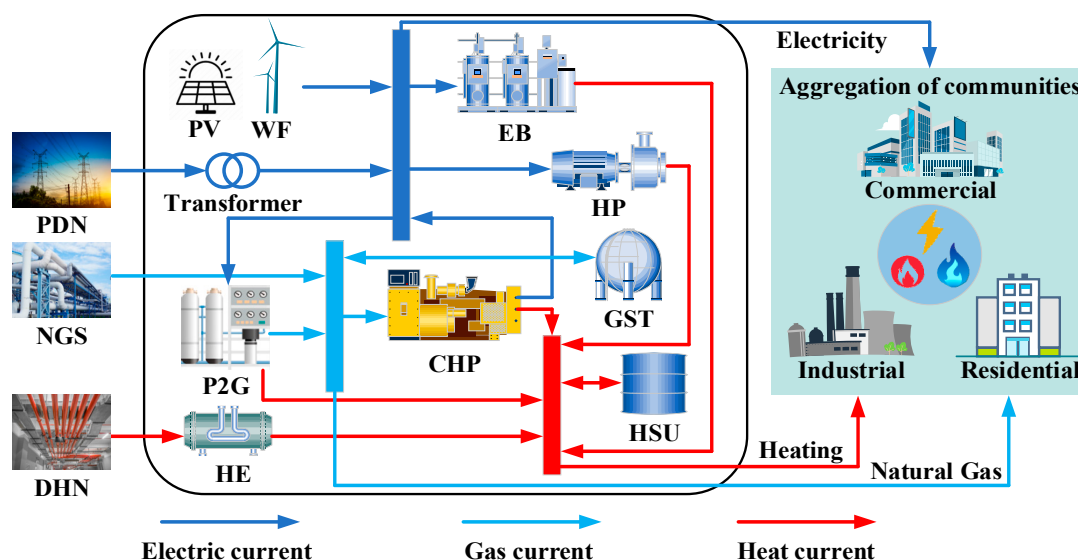


Figure 1. Schematic structure of the CIES.

The PDN, DHN and NGS are generally operated to meet the energy demand by different enterprises, where operational independence must be considered. Based on the strong coupling characteristics of these three systems, CIES is proposed to perform overall collaborative dispatching without different energy systems' fully disclosed operation data and models due to privacy protection. CIES, through the incorporation of prevalent energy production, conversion, and storage technologies like combined heat and power (CHP), heat pumps (HP), power-to-gas (P2G), electric boilers (EB), heat storage units (HSU), and gas storage tanks (GST), offers numerous advantages. It integrates various energy carriers

to meet diverse community user demands, swiftly providing increased flexibility to address real-time energy supply-demand imbalances.

When formulating a schedule for CIES, it is imperative to guarantee energy balance constraints encompassing electricity, natural gas and heat. Thus, the physical model of each part will be formulated separately.

2.1. PDN Model

The nodal power balance constraint is derived from a lossless DC power flow calculation during RT operation, aiming to counter the discrepancy arising from the difference between power consumed and generated in the DA and RT scheduling stages.

$$\sum_{h \in S_{\text{CHP}}} P_{h,t}^{\text{RT}} + \sum_{c \in S_{\text{IC}}} (P_{c,t}^{\text{IMP,RT}} - P_{c,t}^{\text{EXP,RT}}) + \sum_{v \in S_{\text{PV}}} P_{v,t}^{\text{RT}} + \sum_{w \in S_{\text{WF}}} (P_{w,t}^{\text{RT}} - P_{w,t}^{\text{spill}}) + \sum_{e \in S_{\text{ED}}} P_{e,t}^{\text{shed}} = \sum_{e \in S_{\text{ED}}} P_{e,t}^{\text{RT}} + \sum_{d \in S_{\text{CD}}} P_{d,t}^{\text{RT}} + \sum_{j \in S_{\text{PDN}}} B_{ij}(\theta_{i,t}^{\text{RT}} - \theta_{j,t}^{\text{RT}}), \forall i \in S_{\text{PDN}} \quad (1)$$

where $P_{h,t}$, $P_{v,t}$ and $P_{w,t}$ denote the CHP output, PV output and wind farm power output of the t period, respectively; $P_{c,t}^{\text{IMP}}$ and $P_{c,t}^{\text{EXP}}$ represent the imported and exported power at interconnection nodes; $P_{e,t}$, $P_{d,t}$ are the electric demand of load and coupling devices (P2G, EB and HP); B_{ij} is the node admittance matrix and $\theta_{i,t}$ is the phase angle of bus i . In addition, wind spillage $P_{w,t}^{\text{spill}}$ and load shedding $P_{e,t}^{\text{shed}}$ are considered.

The transmission line capacity limit:

$$-P_{ij,t}^{\text{max}} \leq B_{ij}(\theta_{i,t}^{\text{RT}} - \theta_{j,t}^{\text{RT}}) \leq P_{ij,t}^{\text{max}} \quad (2)$$

where $P_{ij,t}^{\text{max}}$ and $-P_{ij,t}^{\text{max}}$ are the maximum and minimum transmission power of the line between the i and j buses.

Phase angle constraint of reference bus:

$$\theta_{\text{ref}} = 0 \quad (3)$$

where θ_{ref} is the angle of the reference bus.

Phase angle constraint of bus i :

$$\theta_i^{\text{min}} \leq \theta_{i,t}^{\text{RT}} \leq \theta_i^{\text{max}} \quad (4)$$

where θ_i^{min} and θ_i^{max} are the upper and lower limits of the bus i phase angle.

The total power provided by the CHP is calculated as a sum of DA value and regulating power. Moreover, coupling devices comprised of EB, HP and P2G units withdraw electrical energy from PDN.

$$P_{h,t}^{\text{RT}} = P_{h,t}^{\text{DA}} + P_{h,t}^{\text{URP}} - P_{h,t}^{\text{DRP}} \quad (5)$$

$$P_{d,t}^{\text{RT}} = P_{b,t}^{\text{EB,RT}} + P_{p,t}^{\text{HP,RT}} + P_{g,t}^{\text{P2G,RT}} \quad (6)$$

where $P_{h,t}^{\text{URP}}$ and $P_{h,t}^{\text{DRP}}$ represent the upward regulating power and downward regulating power, respectively. $P_{b,t}^{\text{EB,RT}}$, $P_{p,t}^{\text{HP,RT}}$ and $P_{g,t}^{\text{P2G,RT}}$ define the electricity consumed by EB, HP and P2G units separately.

Ramping ability constraints of CHP units:

$$P_{h,t}^{\text{RT}} - P_{h,t-1}^{\text{RT}} \leq P_h^{\text{RUR}} \quad (7)$$

$$P_{h,t-1}^{\text{RT}} - P_{h,t}^{\text{RT}} \leq P_h^{\text{RDR}} \quad (8)$$

where P_h^{RUR} and P_h^{RDR} are separately the ramp up rate limit and ramp down rate limit of the generator.

The following constraints ensure that each unit provides regulating power within its ramping rate:

$$0 \leq P_{h,t}^{\text{URP}} \leq P_{h,t}^{\text{URP,max}} \quad (9)$$

$$0 \leq P_{h,t}^{\text{DRP}} \leq P_{h,t}^{\text{DRP,max}} \quad (10)$$

where $P_{h,t}^{\text{URP,max}}$ and $P_{h,t}^{\text{DRP,max}}$ denote maximum limits of the upward regulating power and downward regulating power.

The output of the devices shall not exceed the allowable range of power:

$$P_{h,t}^{\min} \leq P_{h,t}^{\text{RT}} \leq P_{h,t}^{\max} \quad (11)$$

$$P_{d,t}^{\min} \leq P_{d,t}^{\text{RT}} \leq P_{d,t}^{\max} \quad (12)$$

where $P_{h,t}^{\min}$ and $P_{h,t}^{\max}$ represent the minimum and maximum output power of CHP units, $P_{d,t}^{\min}$ and $P_{d,t}^{\max}$ represent the upper and lower bounds of the coupling devices input, respectively.

Limits of the wind spillage and load shedding are established as follows:

$$0 \leq P_{w,t}^{\text{spill}} \leq P_{w,t}^{\text{RT}} \quad (13)$$

$$0 \leq P_{e,t}^{\text{shed}} \leq P_{e,t}^{\text{RT}} \quad (14)$$

Energy interconnections with the external grid are limited as bellow:

$$0 \leq P_{c,t}^{\text{IMP,RT}} \leq P_c^{\text{IMP,max}} x_{c,t}^{\text{IMP}} \quad (15)$$

$$0 \leq P_{c,t}^{\text{EXP,RT}} \leq P_c^{\text{EXP,max}} x_{c,t}^{\text{EXP}} \quad (16)$$

It is worth noting that a binary variable x is introduced in the above model to denote whether interconnection bus is importing or exporting power.

2.2. DHN Model

The DHN distributes the thermal energy produced from heat sources and connects it to community buildings via insulated pipes. The variability in CHP production due to wind uncertainty impacts heat generation in the DHN. This, in turn, alters heat storage input and output values during RT operations compared to those anticipated in the DA stage. Consequently, variations in mass flow and temperature at each node can occur during the RT scheduling phase. This section discusses the detailed modelling of DHN.

2.2.1. Heat Sources

CHP, EB and HP units, serving as most ubiquitous heat sources, establish the connection between the PDN and DHN. Among CHP units, two main types exist based on the steam turbines employed: back-pressure and extraction-condensing. Due to the linear relationship of electric-heating generation, the back-pressure CHP unit is chosen, for example. More precisely, CHP comprises biomass fired plant (BFP), gas fired plant (GFP) and coal fired plant (CFP).

$$H_{h,t}^{\text{CHP,RT}} = \eta_h^{\text{CHP}} P_{h,t}^{\text{RT}} \quad (17)$$

where $H_{h,t}^{\text{CHP,RT}}$ is the heat generated by CHP units and η_h^{CHP} is the thermal power ratio.

Heat storage units (HSU) consist of short-term energy storage devices called hot water tanks (HWT) and long-term energy storage devices called thermal energy storages (TES).

$$H_{s,t}^{\text{HSU,RT}} = H_{s,t}^{\text{dis,RT}} / \eta_s^{\text{dis}} - H_{s,t}^{\text{ch,RT}} \eta_s^{\text{ch}} \quad (18)$$

$$HS_{s,t+1}^{\text{HSU,RT}} = HS_{s,t}^{\text{HSU,RT}} - H_{s,t}^{\text{HSU,RT}} \quad (19)$$

$$HS_s^{\min} \leq HS_{s,t}^{\text{HSU,RT}} \leq HS_s^{\max} \quad (20)$$

$$H_s^{\text{dis,min}} \leq H_{s,t}^{\text{dis,RT}} \leq H_s^{\text{dis,max}} x_{s,t}^{\text{dis}} \quad (21)$$

$$H_s^{\text{ch,min}} \leq H_{s,t}^{\text{ch,RT}} \leq H_s^{\text{ch,max}} x_{s,t}^{\text{ch}} \quad (22)$$

where $HS_{s,t}^{\text{HSU,RT}}$ denotes the thermal energy provided by HSU; $H_{s,t}^{\text{dis,RT}}$ and $H_{s,t}^{\text{ch,RT}}$ are the discharging and charging power of the HSU; η_s^{dis} and η_s^{ch} are the charging and discharging efficiencies; $HS_{s,t}^{\text{HSU,RT}}$ is residual heat energy in the HSU; $HS_s^{\max}/HS_s^{\min}$ is upper/lower limit of $HS_{s,t}^{\text{HSU,RT}}$; $H_s^{\text{dis,max}}/H_s^{\text{dis,min}}$ is upper/lower limit of $H_{s,t}^{\text{dis,RT}}$; $H_s^{\text{ch,max}}/H_s^{\text{ch,min}}$ is upper/lower limit of $H_{s,t}^{\text{ch,RT}}$; binary variables $x_{s,t}^{\text{dis}}$ and $x_{s,t}^{\text{ch}}$ are introduced to prevent simultaneous charging and discharging.

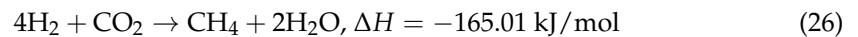
EB and HP are considered as electric loads in PDN, which harness heat energy by consuming. The models of the EB and HP can be written as:

$$H_{b,t}^{\text{EB,RT}} = \eta_b^{\text{EB}} P_{b,t}^{\text{EB,RT}} \quad (23)$$

$$H_{p,t}^{\text{HP,RT}} = \text{COP}_p^{\text{HP}} P_{p,t}^{\text{HP,RT}} \quad (24)$$

where $H_{b,t}^{\text{EB,RT}}$ and $H_{p,t}^{\text{HP,RT}}$ are the heat generated by EB and HP units, η_b^{EB} is electricity to heat efficiency of the EB and COP_p^{HP} is the coefficient of performance of the HP.

The water electrolysis and methanation modules constitute the pivotal elements of P2G units. During the water electrolysis stage, surplus renewable energy is harnessed to decompose water into O_2 and H_2 . At the stage of methanation, the generated H_2 is subsequently combined with CO_2 to produce CH_4 . The formula of the chemical reactions in these two stages are given by:



As the chemical reaction that occurs during the methanation stage of P2G operation is highly exothermic, the generated heat can be used to meet part of the heat demand. The conversion relationship between the CH_4 yield of P2G per unit time and the exothermic reaction is:

$$v_{\text{CH}_4} = \frac{P_{g,t}^{\text{P2G,RT}} / v_{\text{H}_2} \rho_{\text{H}_2}}{4M_{\text{H}_2}} \frac{Q_{\text{CH}_4} / \rho_{\text{CH}_4} M_{\text{CH}_4}}{1000 \times 3600} \quad (27)$$

$$H_{g,t}^{\text{P2G,RT}} = \frac{P_{g,t}^{\text{P2G,RT}} / v_{\text{H}_2} \rho_{\text{H}_2}}{4M_{\text{H}_2}} \frac{\Delta H}{3600} \eta_t^{\text{P2G}} \quad (28)$$

where v_{CH_4} and v_{H_2} denote the methane and hydrogen production, Q_{CH_4} is the heating value of CH_4 , ρ_{CH_4} and ρ_{H_2} are the density of CH_4 and H_2 , M_{CH_4} and M_{H_2} represent the molar mass of CH_4 and H_2 , η_t^{P2G} represents the specific gravity of reaction heat injected into the DHN.

The total thermal energy provided by coupling devices including EB, HP and P2G units can be calculated as below:

$$H_{d,t}^{\text{RT}} = H_{b,t}^{\text{EB,RT}} + H_{p,t}^{\text{HP,RT}} + H_{g,t}^{\text{P2G,RT}} \quad (29)$$

Moreover, flexible heat suppliers (FHS) represent the costliest among heat production units. The aggregated amount of flexible heat producers $H_{f,t}^{\text{flex,RT}}$ is allocated to each area and limited as follows:

$$H_f^{\min} \leq H_{f,t}^{\text{flex,RT}} \leq H_f^{\max} \quad (30)$$

where $H_f^{\max}/H_f^{\min}$ is upper/lower limit of aggregated flexible heat amount.

2.2.2. Pipeline Heating Network

The heat delivered from heat sources are used to satisfy the needs of domestic hot water supply and building space heating which are considered as thermal loads for DHN. The specific modelling of building space heating will be introduced in the next sub-section.

According to the principles of heat exchange theory, the total thermal energy supply and demand at time t can be illustrated as:

$$\sum_{h \in S_{\text{CHP}}} H_{h,t}^{\text{CHP,RT}} + \sum_{s \in S_{\text{HSU}}} H_{s,t}^{\text{HSU,RT}} + \sum_{d \in S_{\text{CD}}} H_{d,t}^{\text{CD,RT}} + \sum_{f \in S_{\text{flex}}} H_{f,t}^{\text{flex,RT}} = c_p m_{i,t}^{\text{G,RT}} (\tau_{i,t}^{\text{S,RT}} - \tau_{i,t}^{\text{R,RT}}) \quad (31)$$

$$\sum_{l \in S_{\text{HL}}} H_{l,t}^{\text{HL,RT}} = c_p m_{i,t}^{\text{D,RT}} (\tau_{i,t}^{\text{S,RT}} - \tau_{i,t}^{\text{R,RT}}) \quad (32)$$

where $H_{l,t}^{\text{HL,RT}}$ denotes the heat load demand; c_p is the specific heat capacity of water; $m_{i,t}^{\text{G,RT}}$ and $m_{i,t}^{\text{D,RT}}$ are the mass flow rate of recycled water from the heat generation unit and the associated heat load at node i ; $\tau_{i,t}^{\text{S,RT}}$ and $\tau_{i,t}^{\text{R,RT}}$ represent temperatures at node i within both the supply water system and the return water system.

Following the principle of flow continuity throughout the entire network, the ensuing equations should be upheld:

$$\sum_{b \in F(i)} m_{b,t}^{\text{S}} + m_{i,t}^{\text{D,RT}} = m_{i,t}^{\text{G,RT}} + \sum_{b \in T(i)} m_{b,t}^{\text{S}}, \forall i, t \quad (33)$$

$$\sum_{b \in F(i)} m_{b,t}^{\text{R}} + m_{i,t}^{\text{G,RT}} = m_{i,t}^{\text{D,RT}} + \sum_{b \in T(i)} m_{b,t}^{\text{R}}, \forall i, t \quad (34)$$

where $m_{b,t}^{\text{S}}$ and $m_{b,t}^{\text{R}}$ are the mass flow rate of recycled water within pipe b ; $F(i)$ and $T(i)$ denote the set of pipes with node i designated as either the 'from' or 'to' node.

The energy conservation law allows the deduction of the mixed fluid's temperature when streams of varying temperatures converge at the confluence node:

$$\sum_{b \in T(i)} (\tau_{b,t}^{\text{S,out}} m_{b,t}^{\text{S}}) = \tau_{i,t}^{\text{S,RT}} \sum_{b \in T(i)} m_{b,t}^{\text{S}} \quad (35)$$

$$\sum_{b \in F(i)} (\tau_{b,t}^{\text{R,out}} m_{b,t}^{\text{R}}) = \tau_{i,t}^{\text{R,RT}} \sum_{b \in F(i)} m_{b,t}^{\text{R}} \quad (36)$$

$$\tau_{b,t}^{\text{S,in}} = \tau_{i,t}^{\text{S,RT}}, \tau_{b,t}^{\text{R,in}} = \tau_{i,t}^{\text{R,RT}} \quad (37)$$

where $\tau_{b,t}^{\text{S,out}}$, $\tau_{b,t}^{\text{R,out}}$ and $\tau_{b,t}^{\text{S,in}}$, $\tau_{b,t}^{\text{R,in}}$ are the temperatures at the outlets and inlets of pipe b in corresponding supply water system and return water system.

In pipes, water temperature diminishes exponentially owing to unavoidable heat dissipation. The relationship between the outlet and inlet temperatures of pipe b is expressed as:

$$\tau_{b,t}^{\text{S,out}} = (\tau_{b,t}^{\text{S,in}} - \tau_t^{\text{am}}) e^{-\lambda_b L_b / (c_p m_{b,t}^{\text{S}})} + \tau_t^{\text{am}} \quad (38)$$

$$\tau_{b,t}^{\text{R,out}} = (\tau_{b,t}^{\text{R,in}} - \tau_t^{\text{am}}) e^{-\lambda_b L_b / (c_p m_{b,t}^{\text{R}})} + \tau_t^{\text{am}} \quad (39)$$

where τ_t^{am} represents the ambient temperature; λ_b signifies the temperature loss coefficient of pipe b , and L_b denotes the length of the pipe.

Heat dissipation within a pipeline can be derived:

$$\Delta H_{b,t}^{\text{S}} = c_p m_{b,t}^{\text{S}} (\tau_{b,t}^{\text{S,in}} - \tau_{b,t}^{\text{S,out}}) \quad (40)$$

$$\Delta H_{b,t}^{\text{R}} = c_p m_{b,t}^{\text{R}} (\tau_{b,t}^{\text{R,in}} - \tau_{b,t}^{\text{R,out}}) \quad (41)$$

Substituting outlet and inlet temperature of pipe into the above equations results in:

$$\Delta H_{b,t}^S = c_p m_{b,t}^S (\tau_{b,t}^{S,in} - \tau_t^{am}) (1 - e^{-\lambda_b L_b / (c_p m_{b,t}^S)}) \quad (42)$$

$$\Delta H_{b,t}^R = c_p m_{b,t}^R (\tau_{b,t}^{R,in} - \tau_t^{am}) (1 - e^{-\lambda_b L_b / (c_p m_{b,t}^R)}) \quad (43)$$

where the exponential term is much less than 1, and according to the equivalence infinitesimal relation $e^{-x} \approx 1 - x$, we obtain:

$$\Delta H_{b,t}^S \approx c_p m_{b,t}^S (\tau_{b,t}^{S,in} - \tau_t^{am}) \frac{\lambda_b L_b}{c_p m_{b,t}^S} = (\tau_{b,t}^{S,in} - \tau_t^{am}) \lambda_b L_b \quad (44)$$

$$\Delta H_{b,t}^R \approx c_p m_{b,t}^R (\tau_{b,t}^{R,in} - \tau_t^{am}) \frac{\lambda_b L_b}{c_p m_{b,t}^R} = (\tau_{b,t}^{R,in} - \tau_t^{am}) \lambda_b L_b \quad (45)$$

2.2.3. Heating Load

The space heating demand pertains to the thermal capacity provided by the DHN to maintain consistent indoor temperature via heating, ventilation, and air-conditioning (HVAC) systems within buildings. Energy consumption patterns due to space heating demand in multi-zone buildings are significantly influenced by regional climate, heat transfer across building structures, daily operations, and occupancy behaviors. Within a zone, two types of nodes exist: wall nodes and room nodes, each characterized by a distinct thermal state. These nodes are linked via thermal resistance and connected to the ground through thermal capacitance. Thermal zones within buildings of similar types exhibit comparable energy consumption by HVAC systems under identical control methods and illumination conditions. Analytically, two differential equations are formulated to represent temperature evolutions of walls and the room.

The specific mathematical correlation between wall temperature, solar radiation energy, and outdoor temperature can be described as follows:

$$\frac{dT_{i,j}^w}{dt} = \frac{1}{C_{i,j}^w} \left(\sum_{j \in S_{i,j}^w} \frac{T_j - T_{i,j}^w}{R_{i,j}^w} + r_{i,j} \alpha_{i,j} A_{i,j}^w H_{i,j}^{rad} \right) \quad (46)$$

where $T_{i,j}^w$ is the wall temperature between neighboring node i and j ; $C_{i,j}^w$ is the thermal capacity of the wall between node i and j ; T_j is the temperature of node j ; $R_{i,j}^w$ represents the thermal resistance between node i and j ; $S_{i,j}^w$ indicates the set of nodes neighboring the wall; binary variable $r_{i,j}$ takes 0 for internal walls and 1 for external walls; $\alpha_{i,j}$ and $A_{i,j}^w$ are the coefficient of radiative heat absorption and the surface area of the wall; $H_{i,j}^{rad}$ is the radiative thermal energy that impinges on the wall.

The thermal equilibrium equation restriction within the room can be formulated as:

$$\frac{dT_i^r}{dt} = \frac{1}{C_i^r} \left(\sum_{j \in S_{i,j}^r} \frac{T_{i,j}^w - T_i^r}{R_{i,j}^w} + \pi_{i,j} \sum_{j \in S_{i,j}^r} \frac{T_j^a - T_i^r}{R_{i,j}^{win}} + H_i^r + H_i^{in} + \pi_{i,j} \tau_{i,j}^{win} A_{i,j}^{win} H_i^{rad} \right) \quad (47)$$

where T_i^r is the temperature of room i ; C_i^r denotes the room thermal capacity; $S_{i,j}^w$ represents the set of all nodes adjacent room i ; window identifier is shown by $\pi_{i,j}$ which equals 0 if there doesn't exist wall between node i and j , otherwise takes 1; T_j^{amb} is the outside ambient temperature; $R_{i,j}^{win}$ is the thermal resistance of window; H_i^r quantifies the indoor consumed thermal energy supplied by DHN. H_i^{in} is the aggregate internal heat gain originating from space heating sources such as occupants and equipment; $\tau_{i,j}^{win}$ is the transmittance of window between node i and j ; $A_{i,j}^{win}$ is the total surface area of window; H_i^{rad} is the total absorbed solar radiation on the window.

The total heat H_i^r consumed by the energy intensive building is derived as follows:

$$H_i^r = m_i^r c_p^{\text{air}} (T_i^s - T_i^r) \quad (48)$$

where m_i^r is the air mass flow; c_p^{air} is the specific heat capacity. T_i^s and T_i^r denote the set point temperature of the supply air and the actual room temperature, respectively.

Given that the operation of the HVAC system should respect the thermal comfort, the indoor temperature of the building could fluctuate in a certain range deviated from the set point.

$$T_i^{\min} \leq T_i^r \leq T_i^{\max} \quad (49)$$

where $T_i^{\min}$ and $T_i^{\max}$ represent the lower and upper indoor temperature bound.

2.3. NGS Model

The flow of natural gas is propelled by the pressure generated by gas compressors situated along the pipelines. These compressors are installed to counteract the loss of gas pressure caused by frictional resistance within the pipelines. This ensures that the gas can reach the end nodes within the specified pressure limits, guaranteeing effective gas delivery across the network. Due to the compressibility of the natural gas, a certain amount of gas can be stored in the pipe, which is termed as linepack. In NGS, linepack storage plays a pivotal role in flexible and reliable operation for alleviating the spatial-temporal mismatch between gas sources and loads. Thus, we dispatch the NGS with a steady-state isothermal natural gas flow model accounting for linepack in pipelines.

According to the Weymouth equation, the correlation between nodal natural gas pressure and pipeline natural gas flow can be described as:

$$(S_{mn,t}^{\text{RT}})^2 = C_{mn} [(p_{m,t}^{\text{RT}})^2 - (p_{n,t}^{\text{RT}})^2] \quad (50)$$

where $S_{mn,t}^{\text{RT}}$ is the gas flow rate in pipeline between node m and n ; C_{mn} is the Weymouth constant of the pipeline; $p_{m,t}^{\text{RT}}$ is the nodal natural gas pressure of node n .

The nodal gas balancing equation is depicted as follows:

$$\begin{aligned} & \sum_{w \in S_{\text{GW}}} Q_{w,t}^{\text{GW,RT}} + \sum_{s \in S_{\text{ST}}} (Q_{s,t}^{\text{ST,out,RT}} - Q_{s,t}^{\text{ST,in,RT}}) + \sum_{i \in S_{\text{ICG}}} (Q_{i,t}^{\text{IMP,RT}} - Q_{i,t}^{\text{EXP,RT}}) \\ & + \sum_{g \in S_{\text{P2G}}} Q_{g,t}^{\text{P2G,RT}} - \sum_{h \in S_{\text{CHP}}} D_{h,t}^{\text{CHP,RT}} - \sum_{c \in S_{\text{GC}}} D_{c,t}^{\text{GC,RT}} = \sum_{m \in S_{\text{NGS}}} S_{mn,t}^{\text{RT}} \end{aligned} \quad (51)$$

where $Q_{w,t}^{\text{GW}}$ is the gas well output; $Q_{s,t}^{\text{ST,out}}$ and $Q_{s,t}^{\text{ST,in}}$ are the quantity of gas supplied to or withdrawn from GST at time period t ; $Q_{i,t}^{\text{IMP}}/Q_{i,t}^{\text{EXP}}$ is imported/exported gas power from/to the gas interconnection(ICG) node i ; $Q_{g,t}^{\text{P2G}}$ is the gas produced by P2G unit while $D_{h,t}^{\text{CHP}}$ and $D_{c,t}^{\text{GC}}$ are gas consumed by CHP unit and gas compressor (GC).

Upward reserves $Q_{g,t}^{\text{P2G,URP}}$ and downward reserves $Q_{g,t}^{\text{P2G,DRP}}$ offered by P2G are employed to provide regulating power.

$$Q_{g,t}^{\text{P2G,min}} \leq Q_{g,t}^{\text{P2G,RT}} = Q_{g,t}^{\text{P2G,DA}} + Q_{g,t}^{\text{P2G,URP}} - Q_{g,t}^{\text{P2G,DRP}} \leq Q_{g,t}^{\text{P2G,max}} \quad (52)$$

where $Q_{g,t}^{\text{P2G,min}}$ and $Q_{g,t}^{\text{P2G,max}}$ denote the lower and upper limit of P2G output.

The operational boundaries for gas consumption from the source, pipeline pressure, and gas flow within the pipeline are subject to constraints:

$$Q_{w,t}^{\text{GW,min}} \leq Q_{w,t}^{\text{GW,RT}} \leq Q_{w,t}^{\text{GW,max}} \quad (53)$$

$$p_m^{\min} \leq p_{m,t}^{\text{RT}} \leq p_{m,t}^{\max} \quad (54)$$

$$-S_{mn}^{\max} \leq S_{mn,t}^{\text{RT}} \leq S_{mn}^{\max} \quad (55)$$

where $Q_{w,t}^{GW,min}/Q_{w,t}^{GW,max}$ is lower/upper limit of $Q_{w,t}^{GW,RT}$; p_m^{min} and p_m^{max} refer to the lower and upper pressure bounds; S_{mn}^{max} enforces the capacity for gas flow at pipeline mn .

The RT amount of gas storage $GS_{s,t}^{RT}$ in GST primarily relies on the initial gas quantity within the tank and discharging/charging power.

$$GS_{s,t+1}^{RT} = GS_{s,t}^{RT} + Q_{s,t}^{ST,out,RT} - Q_{s,t}^{ST,in,RT} \quad (56)$$

$$0 \leq Q_{s,t}^{ST,in,RT} \leq Q_{s,t}^{ST,in,max} x_{s,t}^{ST,in,RT} \quad (57)$$

$$0 \leq Q_{s,t}^{ST,out,RT} \leq Q_{s,t}^{ST,out,max} x_{s,t}^{ST,out,RT} \quad (58)$$

$$x_{s,t}^{ST,in,RT} + x_{s,t}^{ST,out,RT} \leq 1 \quad (59)$$

$$GS_s^{min} \leq GS_{s,t}^{RT} \leq GS_s^{max} \quad (60)$$

where binary variables $x_{s,t}^{ST,in,RT}/x_{s,t}^{ST,out,RT}$ are used to ensure the mutual exclusiveness of GST charging/discharging in the RT stage; GS_s^{min} and GS_s^{max} are lower and upper limit of the GST capacity.

ICG importing/exporting processes will never occur simultaneously during the RT scheduling:

$$0 \leq Q_{i,t}^{IMP,RT} \leq Q_i^{IMP,max} x_{i,t}^{IMP,RT} \quad (61)$$

$$0 \leq Q_{i,t}^{EXP,RT} \leq Q_i^{EXP,max} x_{i,t}^{EXP,RT} \quad (62)$$

where $Q_i^{IMP,max}/Q_i^{EXP,max}$ denotes maximum imported/exported power limit of ICG capacity; The limitation imposed on the sum of $x_{i,t}^{IMP,RT}$ and $x_{i,t}^{EXP,RT}$ indicates that ICG cannot import and export power concurrently.

Compressors in the NGS are commonly utilized to boost pressure and facilitate gas transportation:

$$D_{c,t}^{GC,RT} = K^{GC} Z_a \frac{T_s}{E^{GC} \eta^{GC}} \frac{c_k}{c_k - 1} (CR^{\frac{c_k}{c_k-1}} - 1) S_{c,t}^{GC,RT} \quad (63)$$

$$(p_{n,t}^{RT})^2 \leq CR^2 (p_{m,t}^{RT})^2 \quad (64)$$

where K^{GC} is the constant employed for gas flow; Z_a is the average compressibility factor. T_s is the suction temperature. E^{GC} , η^{GC} and c_k are grounded on an assumption for the centrifugal unit, representing parasitic efficiency, compression efficiency constant, and specific heat, respectively. CR represents the gas compression ratio.

The linepack model indicating the pipeline storage capacity can be assessed by:

$$l_{mn,t}^{RT} = \frac{\pi D_{mn}^2}{4RTZ_a\rho_0} \frac{p_{m,t}^{RT} - p_{n,t}^{RT}}{2} \quad (65)$$

$$l_{mn,t}^{RT} = l_{mn,t-1}^{RT} + S_{mn,t}^{in,RT} - S_{mn,t}^{out,RT} \quad (66)$$

where D_{mn} is the diameter of the pipeline; R is the molar gas constant; T is the gas temperature; ρ_0 is the gas density under standard condition; $S_{mn,t}^{in,RT}$ and $S_{mn,t}^{out,RT}$ are the inlet and outlet gas flow rates of the pipe, respectively.

It is worth mentioning that the two equations above describe the linepack from different perspectives, the first equation indicates that the linepack of a specific pipeline is proportional to the average pressure and the pipe characteristics whereas the second equation complies with the mass conservation.

To make the optimization problem computationally tractable, linearization procedure is performed. The pipeline flow equation, encapsulated within the Weymouth equation, involves multiple square terms, leading to non-convex elements that elevate computa-

tional complexity. Utilizing the incremental formulation allows for piecewise linearization, nonlinear terms in the gas flow equation are univariate and separable.

Given the squared pressure and known flows, π_m substitutes for the pressure at each node. The quadratic flow on the equation's left side is subsequently approximated by a piecewise linear function $h(x)$ as outlined below.

$$(S_{mn,t}^{\text{RT}})^2 = C_{mn}(\pi_{m,t}^{\text{RT}} - \pi_{n,t}^{\text{RT}}) \quad (67)$$

$$h(S_{mn,t}^{\text{RT}}) = (S_{mn,t}^{\text{RT}})^2 \quad (68)$$

$$h(S_{mn,t}^{\text{RT}}) \approx h(S_1) + \sum_{i=1}^P [h(S_{i+1}) - h(S_i)]\delta_i, \forall i \in P \quad (69)$$

$$S_{mn,t}^{\text{RT}} = S_1 + \sum_{i=1}^P (S_{i+1} - S_i)\delta_i, \forall i \in P \quad (70)$$

$$-S_{mn}^{\max} \leq S_i \leq S_{mn}^{\max}, \forall i \in P \quad (71)$$

$$0 \leq \delta_i \leq 1, \forall i \in P \quad (72)$$

$$x_i \leq \delta_i, x_i \geq \delta_{i+1}, \forall i \in P - 1 \quad (73)$$

$$x_i \in \{0, 1\}, \forall i \in P - 1 \quad (74)$$

$$0 \leq \delta_i \leq 1, \forall i \in P \quad (75)$$

where the feasible region is partitioned into P piecewise linear segments, delineated by a grid of S_i points. Binary variable x_i determines which linear segment the variable falls in; continuous variable δ_i is the portion of each segment.

Regarding the DHN, the bilinear product terms detailed in (31)–(39), undergo linearization through the binary expansion method [32]. This transformation restructures the optimization problem into MILP. Nonetheless, ensuring a viable solution across the complete scheduling horizon remains imperative. Therefore, the framework of SMPC-based multi-temporal-spatial-scale flexibility scheduling strategy is proposed in the following section to achieve optimal planning and scheduling of the CIES.

3. Framework of SMPC-Based Multi-Temporal-Spatial-Scale Flexibility Scheduling Strategy

The multi-temporal-spatial-scale flexibility scheduling of CIES is essential to ensure optimal utilization of RES and meet dynamic energy demands, thereby enhancing system reliability, resilience, and sustainability. On one hand, the temporal unpredictability and uncertainty for system load and RES output would result in a considerable risk of energy supply. To elaborate, the instability of system load and RES output covers minutely and hourly fluctuation, DA and RT intermittency, and imbalance in different seasons. This characteristic leads to the demand for system flexibility and encompassing multiple temporal scales to secure a stable and reliable energy system. On the other hand, community building thermal inertia can provide a great deal of flexibility in the system but is largely influenced by the building envelope. Hence, the spatially varying influence of building envelope structures is supposed to be urgently examined to better investigate the thermal inertia potential of different communities. Under such circumstance, the multi-temporal-spatial-scale method is particularly suitable for offering flexibility while concurrently improving the efficiency of the CIES. In this paper, the spatial scale of the system can be divided by the holistic scheduling of CIES and the detailed analysis of heterogeneous communities (e.g., residential, commercial, and industrial), while the temporal scale of the system is decomposed into day-ahead and real-time scheduling stages.

Conventional RT scheduling optimizes a single scheduling period without considering future uncertainty information, relying solely on the measured uncertainty value at the current time step. In contrast, MPC strategy presents an optimal control method

aimed at ensuring the total operational cost of CIES is minimized while satisfying all security constraints. The primary challenge of this strategy revolves around ensuring power equilibrium among multiple carriers, requiring the establishment of a prediction horizon, continuous updates of system values, and the derivation of optimal solutions at each time interval.

However, future predictions boil down to be deterministic and unable to accurately depict the actual uncertainties, which may violate the state constraint within MPC. Conversely, the stochastic programming technique encapsulates potential future realizations along with their respective probabilities. Hence, an SMPC-based multi-temporal-spatial-scale flexibility scheduling strategy is employed, accounting for multiple uncertainty sources which include power demand, solar PV output and wind power generation.

3.1. Auto-Regressive Model for Prediction Horizon

Aiming to forecast the future data concerning multiple uncertainty sources in the proposed SMPC method, an auto-regressive model is adopted due to its high accuracy in control strategies with fine time discretizations. The autoregressive model of order p is denoted by Equation (76) and its concise representation is given by Equation (77).

$$y_t = \beta_{t,0} + \beta_{t,1}y_{t-1} + \beta_{t,2}y_{t-2} + \dots + \beta_{t,p}y_{t-p} + \varepsilon_t, \forall t \quad (76)$$

$$y_t = \beta_t^T x_t + \varepsilon_t, \forall t \quad (77)$$

where y_t is the random response variable which can quantify uncertainty at time t ; $\beta_t = [\beta_{t,0}, \beta_{t,1}, \dots, \beta_{t,p}]^T$ is the model parameter; $x_t = [1, y_{t,1}, \dots, y_{t,p}]^T$ is the explanatory variable and ε represents the noise considering the discrepancy between the measured data and the formulated model. In this way, the recursivity of the autoregressive model is controlled by the order of the model.

To estimate model parameters β_t , the regressive least square (RLS) method is applied as presented in Equation (78).

$$\hat{\beta}_t = \underset{\beta}{\operatorname{argmin}} S_t \beta = \underset{\beta}{\operatorname{argmin}} \frac{1}{2} \sum_{i < t} \lambda^{t-i} (y_i - \beta^T x_i)^2 \quad (78)$$

where λ is the forgetting factor with a value less than 1 and close to 1. An update for $\hat{\beta}_t$ can be recursively obtained through the Newton–Raphson method:

$$\hat{\beta}_t = \hat{\beta}_{t-1} - \frac{\nabla S_t(\hat{\beta}_{t-1})}{\nabla^2 S_t(\hat{\beta}_{t-1})} \quad (79)$$

Following Equation (78), derivatives are acquired to obtain the update scheme for RLS. Assuming that the current step is $t - 1$ and the future step is t , $S_t(\hat{\beta}_{t-1})$ is rewritten as:

$$S_t(\hat{\beta}_{t-1}) = \lambda S_{t-1}(\hat{\beta}_{t-2}) + \frac{1}{2} (y_t - \hat{\beta}_{t-1}^T x_t)^2 \quad (80)$$

The first derivative is applied on both sides of Equation (80) resulting in:

$$\nabla S_t(\hat{\beta}_{t-1}) = \lambda \nabla S_{t-1}(\hat{\beta}_{t-2}) - x_t (y_t - \hat{\beta}_{t-1}^T x_t) \quad (81)$$

The second derivative on Equation (81), results in Equation (82). To simplify the notation, R_t and R_{t-1} are introduced to denote similar parts.

$$R_t = \nabla^2 S_t(\hat{\beta}_{t-1}) = \lambda \nabla^2 S_{t-1}(\hat{\beta}_{t-2}) + x_t x_t^T \quad (82)$$

$$R_{t-1} = \nabla^2 S_{t-1}(\hat{\beta}_{t-2}) \quad (83)$$

Then the recursive equation for R_t is obtained:

$$R_t = \lambda R_{t-1} + x_t x_t^T \quad (84)$$

Substituting R_t into the denominator in Equation (79), recursive $\hat{\beta}_t$ can be further derived:

$$\hat{\beta}_t = \hat{\beta}_{t-1} + R_t^{-1} x_t (y_t - \hat{\beta}_{t-1}^T x_t) \quad (85)$$

The flow chart to recursively estimate the parameters $\hat{\beta}_t$ by applying RLS is presented in Figure 2. Firstly, historical data are obtained. Secondly, order p for Equation (77) is decided. Thirdly, the forgetting factor λ is determined, then R_{t-1} and β_{t-1} are set to zeros initially. In step 1, the first two values of time series in the historical data are left outside as the order p equals two and those first two values are used as input in the first loop in step 1. After step 1 is completed and initial parameters are obtained, the learning step is no longer needed. Step 2 can be applied providing the future forecasted values.

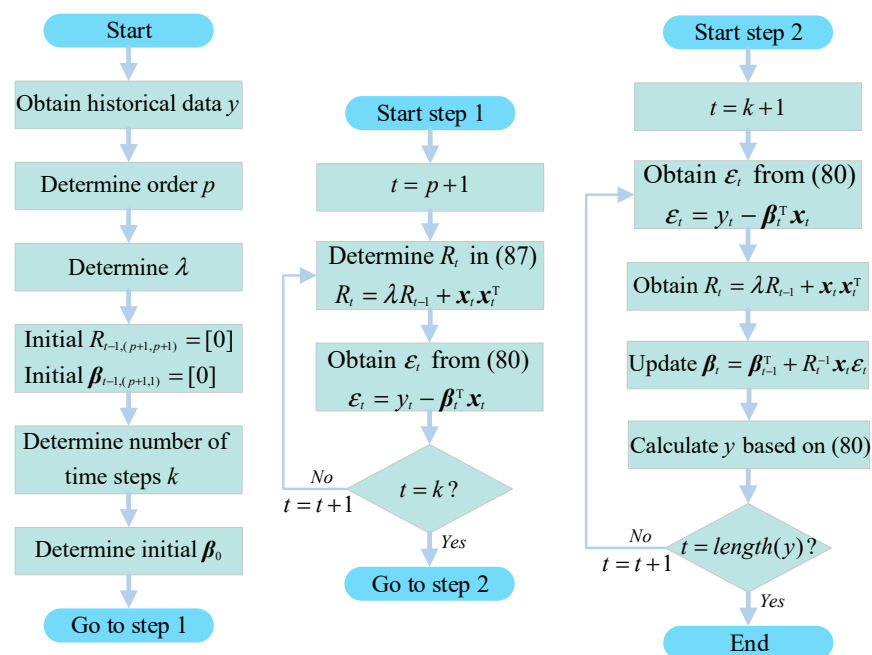


Figure 2. Flow chart of the auto-regressive model.

3.2. SMPC for the System with Uncertainty

The inherent stochasticity of SMPC method is represented by the scenario generation technique based on historical measurements. An empirical cumulative distribution function (ECDF) of recorded historical data, considering temporal correlation, is applied. In this study, both the measured and forecasted data of uncertainty sources should be included. Thus, the research and analysis of this work is founded on the available historical observations queried from [33]. The data are captured at 15-min intervals, generating 96 measurements per day and thus resulting in 96-point predictions for each scenario.

Given that historical measurements do not align well with the theoretical distributions, an ECDF non-parametric estimate is created to characterize uncertainty. The ECDF F does not assume any particular theoretical distribution and instead relies on historical measurements, which will be used as inputs to scenario generation.

To arrive at the formulation of the scenario generation mechanism, the inverse transform method is applied to sample random response variable y_t . The inverse transform method is described as:

$$y_t = F^{-1}(U) \quad (86)$$

where F^{-1} is the inverse function of F and U is uniformly distributed on $[0,1]$. By introducing a new random variable Z_t which follows the standard normal distribution with zero mean and unit standard deviation, the uniform distribution U can be replaced by $\Phi(Z_t)$:

$$\Phi(Z_t) = \int_{-\infty}^{Z_t} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \quad (87)$$

$$y_t = F^{-1}(\Phi(Z_t)) \quad (88)$$

After introducing the inverse transform method, the stochastic process can be transformed into a Gaussian random vector $\mathbf{Z} = (Z_1, Z_2, \dots, Z_K)^T$ subject to a multivariate zero-mean normal distribution with a covariance matrix, abbreviated by $N(0, \Sigma)$. To calculate the covariance matrix, parameter δ within the equation is employed to numerically compute the covariance matrix, effectively governing the interrelation of the two stochastic time variables for generated scenarios. The covariance matrix is a positive definite matrix where K is the maximum prediction horizon, which satisfies:

$$\Sigma = \begin{bmatrix} \sigma_{1,1} & \sigma_{1,2} & \cdots & \sigma_{1,K} \\ \sigma_{2,1} & \sigma_{2,2} & \cdots & \sigma_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{K,1} & \sigma_{K,2} & \cdots & \sigma_{K,K} \end{bmatrix} \quad (89)$$

where covariance σ is

$$\sigma_{R_i, R_j} = \text{cov}(R_i, R_j) = e^{-\frac{|i-j|}{\delta}}, \quad 0 \leq i, j \leq K \quad (90)$$

R represents stochastic variables. Upon obtaining the covariance matrix, the generation of the Gaussian random vector is facilitated. For every individual point forecast, 500 scenarios are constructed, which yields a vector size of $[500, 96]$ for the generated scenarios. Subsequently, the backward scenario reduction method is performed to decrease the initial count of scenarios without unacceptable loss in accuracy. These scenarios will subsequently be employed in the stochastic optimization problem elaborated below.

3.3. Application of Proposed Method

A schematic overview of the application of proposed method is summarized in Figure 3. As illustrated in Figure 3, the SMPC method iteratively computes an optimized control policy for each time period throughout the scheduling horizon, executing the initial control action from the prediction horizon sequentially.

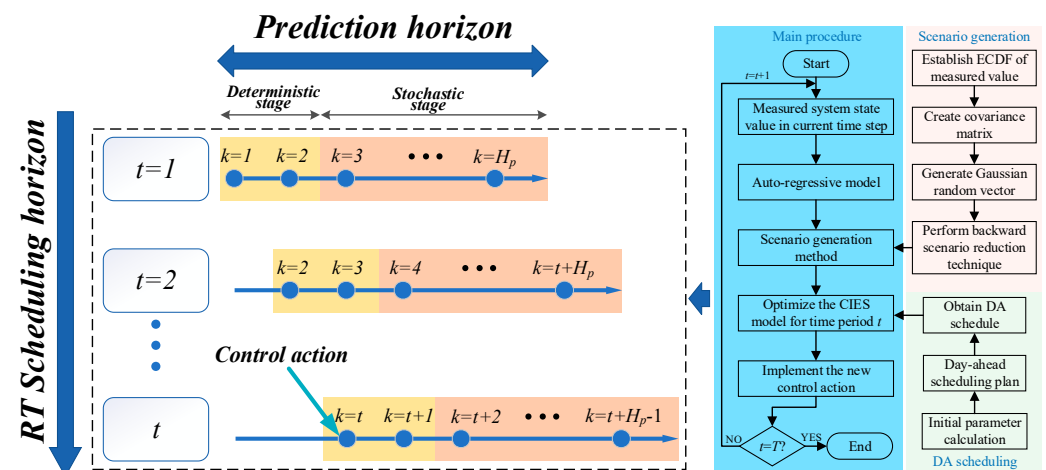


Figure 3. Principle of the application of the proposed method.

In this study, both scheduling and prediction horizon are considered in an uncertain environment. In the context of the SMPC-based real-time scheduling, let us consider a prediction horizon t comprising H_p time steps. The initial time step within the prediction horizon employs actual measurements of uncertainty sources (offshore and onshore wind farm generation, solar PV output, and electric demand). Subsequent to the first time step, forecast data of respective uncertainty source, derived from the auto-regressive model developed in Section 3.1, are leveraged. For the rest $H_p - 2$ time steps, the predictions are derived through scenario generation method developed in Section 3.2. Given the real-time feasibility of the proposed technique and the computation duration of the stochastic optimization problem at each step, the scenario count is established at 6 [34], ensuring practical implementation. Once the day-ahead scheduling is performed with a time scale of 1 h and the initial scheduling scheme is obtained, the main procedure of the SMPC-based scheduling strategy can be conducted sequentially. The first stage of prediction horizon is deterministic and accounts for measurements and predictions, whereas the second stage is stochastic and generated scenario will furnish the SMPC with details regarding potential alternatives for the upcoming uncertainty patterns. Based on the solution process of the proposed method, we can minimize the total operational cost of CIES model as established in Section 2 throughout the whole scheduling period.

3.4. Objective Function and Joint Optimal Control Problem

The proposed scheduling strategy aims to solve a joint optimal control problem on a rolling horizon basis. From the preceding models and the operational dynamics of the CIES, the objective function aims to minimize the total anticipated operational expenses across the entire system. As mentioned earlier in the end of Section 3.3, the first stage of objective function is a deterministic problem, while the second stage is a stochastic optimization problem and depends on the probability of scenario occurring π_ω .

$$\min \underbrace{\sum_{k=t}^{t+H_{p_1}-1} \left\{ \begin{aligned} &\sum_{h \in S_{CHP}} C_h^{CHP} + \sum_{s \in S_{HSU}} C_s^{HSU} + \sum_{w \in S_{GW}} C_w^{GW} + \sum_{s \in S_{ST}} C_s^{ST} + \sum_{g \in S_{P2G}} C_g^{P2G} + \sum_{d \in S_{CD}} C_d^{DA} \\ &+ \sum_{c \in S_{IC}} C_c^{IC} + \sum_{i \in S_{ICG}} C_i^{ICG} + \sum_{f \in S_{flex}} C_f^{flex} + \sum_{c \in S_{GC}} C_c^{GC} + \sum_{v \in S_{PV}} C_v^{DA} + \sum_{w \in S_{WF}} C_w^{DA} \end{aligned} \right\}}_{\text{first stage: deterministic problem}} \quad (91)$$

$$+ \underbrace{\sum_{\omega \in \Phi} \pi_\omega \sum_{k=t+H_{p_1}}^{t+H_p-1} [C^{\text{penalty}}(\text{RT} - \text{DA}) + \sum_{w \in S_{WF}} C_w^{\text{spill}} + \sum_{e \in S_{ED}} C_e^{\text{shed}}]}_{\text{second stage: stochastic problem}}, \forall t \in T, k \in K$$

where k denotes the time step index within a prediction horizon and H_{p_1} represents the length of deterministic prediction horizon. As an important part of the objective function, the penalties for variances between the RT and DA values are incorporated to reduce the regulation cost of generators. Notably, the optimization problem is addressed individually for each time period t , considering all constraints within the prediction horizon for each time step. In RT dispatch, the constraints include PDN (1)–(16), DHN (17)–(49), NGS (50)–(66) and corresponding linearization constraints. It is noteworthy that the optimization model is formulated as a MILP model that is numerically solvable.

4. Simulation Results and Discussion

The illustrated test system topology in Figure 4 combines a modified IEEE 33-bus PDN, a 33-node DHN, and a 52-node NGS, aiming to validate the feasibility of the model and the proposed strategy in this paper. The base power of the proposed CIES is 1000 MVA, base voltage of PDN is 400 kV and base pressure of NGS is 1 MPa. Nodes 26, 48 in the NGS and Buses 1, 4, 6, 9, 12 in the PDN are selected as interconnection nodes to enable the procurement and sale of natural gas and electricity. Natural gas, heat and electrical load profiles have been sourced from [35] and [36]. The parameters pertaining to the NGS and DHS can be referenced from [35] and [37], respectively. To align with the real-time

resolution of 15 min, the original gas and heat load datasets have been extended to 96 time steps, with equal values maintained for each hour.

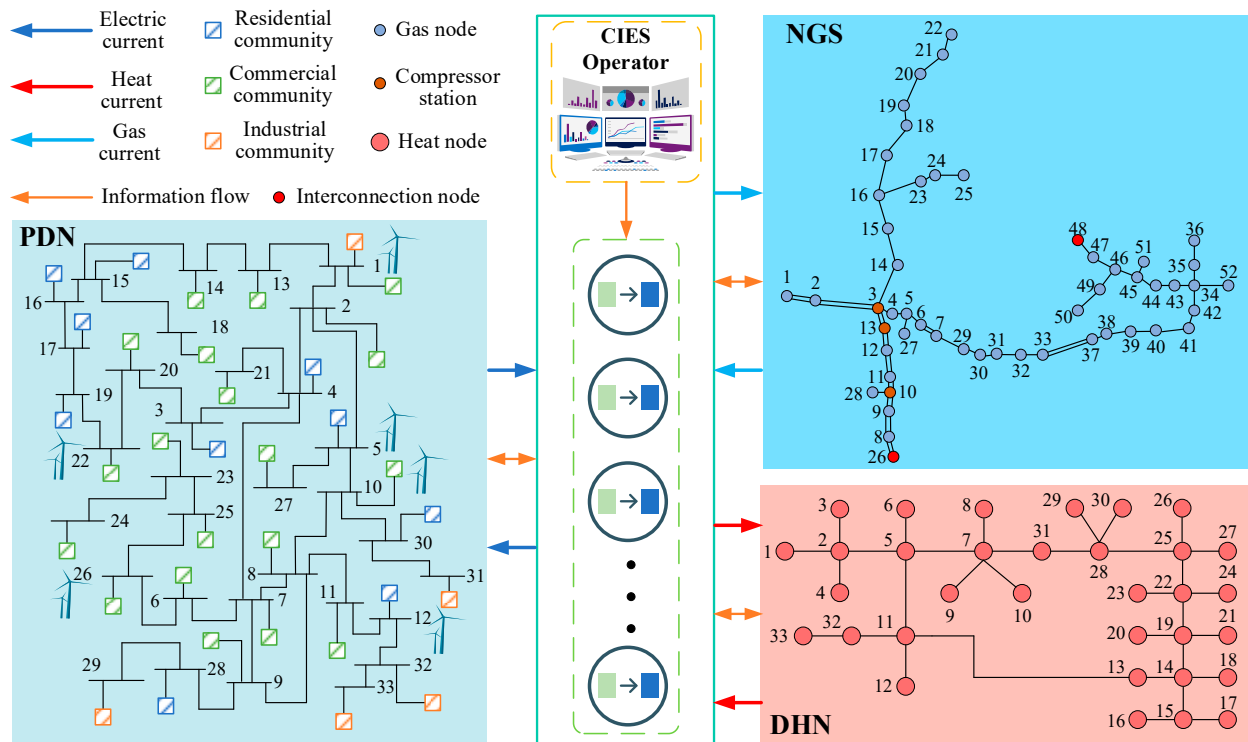


Figure 4. Topology of the test system.

In the depicted topology, there are two keys to realize the advantages of multi-energy complementation, including physical interconnection and information interconnection. Physical interconnection is established based on diversified energy currents and energy networks to achieve goals of economically, efficiently and safely increasing the dynamic balance of electricity, heat and gas. Information interconnection is used to enhance the reliability of energy supply when a certain type of energy fails or is in short supply. In this case, 33 CIES with different configurations are built according to the location of communities in the PDN. With respect to the CIES and whole energy system, the key technical parameters are presented in Table 1. The detailed parameters of the CIES are listed in Table A1 of Appendix A.

Table 1. Technical parameters of the test system.

Parameters	Values	Parameters	Values
BFP efficiency	0.85	HWT of CHP	[0, 0.175]
GFP heat efficiency	0.38	TES output	[0, 0.45]
P2G efficiency	0.7	Gas source output	[0, 20.32]
GFP electric efficiency	0.4	Z_a	0.95
CFP efficiency	0.7	K^{GC}	0.0854
TES charging efficiency	0.95	E^{GC}	0.99
TES discharging efficiency	0.95	η^{GC}	0.85
EB efficiency	0.99	c_k	1.3
P2G heat efficiency	0.08	Molar gas constant	500

The DA plan spans 24 h at hourly intervals, while the RT schedule covers 24 h at 15 min intervals. Computational tasks are executed on a 3.20 GHz Windows laptop equipped with 16 GB RAM, utilizing MATLAB. To optimize accuracy and efficiency, the YALMIP toolbox and solver CPLEX are employed for solving the MILP model. The

solved MILP model involves a total of 60 real-type semidefinite programming variables, out of which 14 are binary decision variables. Additionally, there are 4 N-dimensional semidefinite programming variables, representing multi-dimensional objects. The entire problem comprises a total of 50,246 constraints, including 19,248 equality constraints and 30,998 element-wise inequality constraints.

The operation scenario selected for the case study is a winter operation scenario. The solar radiation intensity and the ambient temperature profiles of a typical winter day used in DA and RT scheduling are shown in Figure 5.

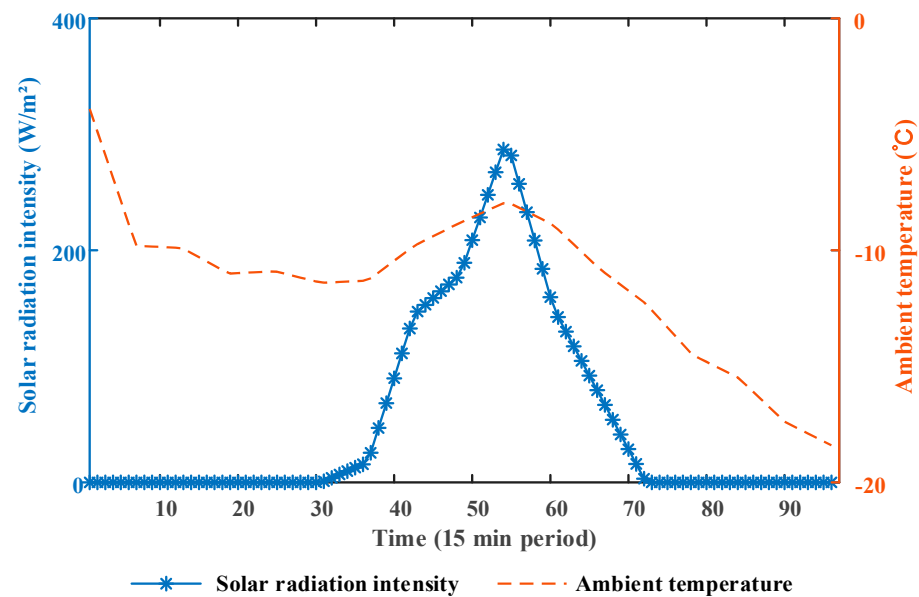


Figure 5. Solar radiation and ambient temperature.

4.1. Validation of the SMPC Strategy

By incorporating uncertainty into the model, the SMPC strategy can provide more accurate predictions and better control performance. In order to quantitatively evaluate the performance of the proposed strategy and reflect the uncertainty of load and RES, three indices are calculated and then compared based on the results from the simulation.

In Figure 6, the simulation results illustrate the forecasting capabilities of the proposed approach alongside a representative SMPC method developed in [38] and an MPC model established in [39], under various characteristic uncertain patterns. In these diagrams we observe the expected forecast of different methods almost perfectly reproduce the characteristics of the actual data while maintaining its diversity, and thereby fully representing the practical operating conditions of these four uncertainty sources. Table 2 compares the prediction accuracy for multiple uncertainty sources under different methods based on the R-Square metric. It can be observed that, for electric demand and PV generation, the proposed SMPC method demonstrates superior performance, while in the case of wind power generation, the typical SMPC method excels. The MPC method exhibits relatively lower R-Square values across all uncertainty sources, indicating comparatively poorer performance.

To clearly show the curves of comparison results, the ideal fit line (dashed black line) and the regression line (red line) are plotted to show the proximity of forecasted value and actual value in Figure 7. Take electric demand as an example, the Pearson's r value between the forecasted and actual values is 0.99021 at a 95% confidence level, representing a strong positive linear correlation between the two values. Additionally, the coefficient of determination (COD or R-Square) is 0.98052, indicating that approximately 98% of the variability in the actual values can be explained by the forecasted values.

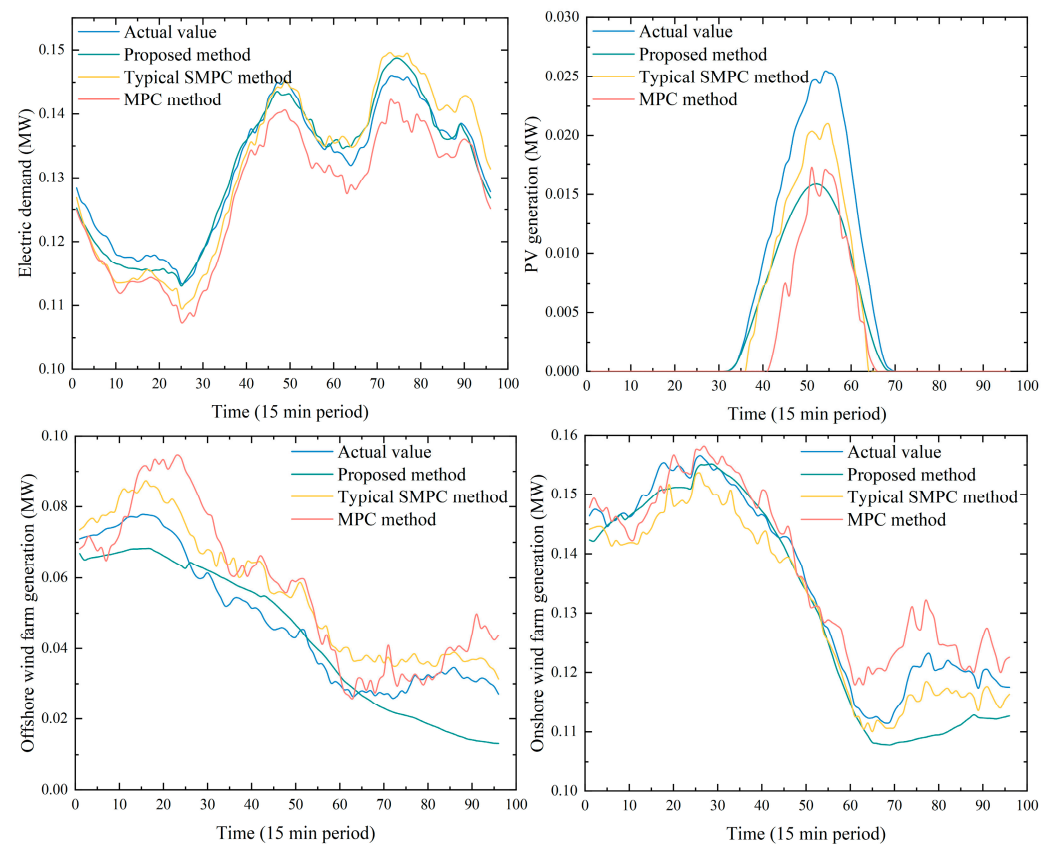


Figure 6. Comparison of the actual and forecasted values of multiple uncertainty sources.

Table 2. Prediction accuracy for multiple uncertainty sources under different methods.

Methods	Electric Demand	PV Generation	Wind Onshore	Wind Offshore
Proposed SMPC	0.98052	0.98735	0.97011	0.95660
Typical SMPC	0.97338	0.98557	0.98934	0.97412
MPC	0.96564	0.94850	0.95816	0.86153

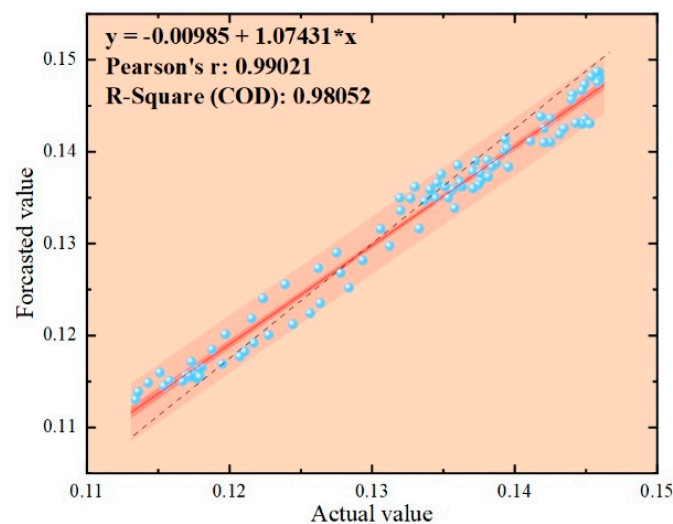


Figure 7. Linear regression analysis of electric demand.

Besides, root mean squared error (RMSE) is also applied as one of the forecasting performance indices. The values of the three indices for each uncertainty source are listed

in Table 3. As shown in Table 3, the proposed approach is highly accurate and reliable, as exemplified by the close to zero RMSE, strong positive correlation demonstrated by high Pearson's r , and high explained variability shown by COD (R-Square) value approaching 1, which can effectively forecast the actual values based on the measured data. The prediction accuracy of offshore wind power is lower compared to the onshore wind power due to a higher forecast error of offshore wind power.

Table 3. Three indices for uncertainty sources.

Indices	Electric Demand	Wind Onshore	Wind Offshore	PV Generation
Pearson's r	0.99021	0.98494	0.92553	0.99366
COD	0.98052	0.97011	0.8566	0.98735
RMSE	2.96184×10^{-6}	2.88237×10^{-5}	7.89521×10^{-5}	1.36794×10^{-5}

4.2. Day-Ahead Scheduling Analysis

In the day-ahead stage, this paper performs robust scheduling on a large temporal and spatial scale for CIES. The optimal scheduling results for the energy flows in PDN, DHN and NGS are depicted in Figures 8–10, respectively.

As illustrated in Figure 8, the electrical demand is primarily supplied by CHP units and renewable energy sources to build a nearly zero-energy district. Regarding the low-price electrical energy in periods of 01:00–10:00, EBs and HPs are dispatched to meet the increasing heat demand, while the surplus wind power is consumed by P2G units. In periods of high electricity prices, such as 11:00–22:00, CHP output increases with the decrease in EB and HP input, and the shortage is satisfied by wind and PV generation. It is noteworthy that the total imported power from interconnection nodes is 0.6488 MW at peak hours, which is insignificant compared to other power sources.

The heat energy dispatch results are plotted in Figure 9. The high heating demand in winter is mainly met by CHP, EB and HP. Additionally, flexible heat suppliers provide a small portion of the heating demand. The discharging power of HWT located near the CHP units is relatively low from 01:00 to 10:00. In addition, the advantage of large capacity TES in improving CIES operation coordination and stability is also reflected in the figure. For the gas energy supply and demand in Figure 10, the CIES mostly satisfies the gas demand by gas source, while the shortage is alleviated by GST, P2G and imported gas. Likewise, a fraction of the gas is exported when the gas load demand gets elevated during valley hours 1:00–9:00.

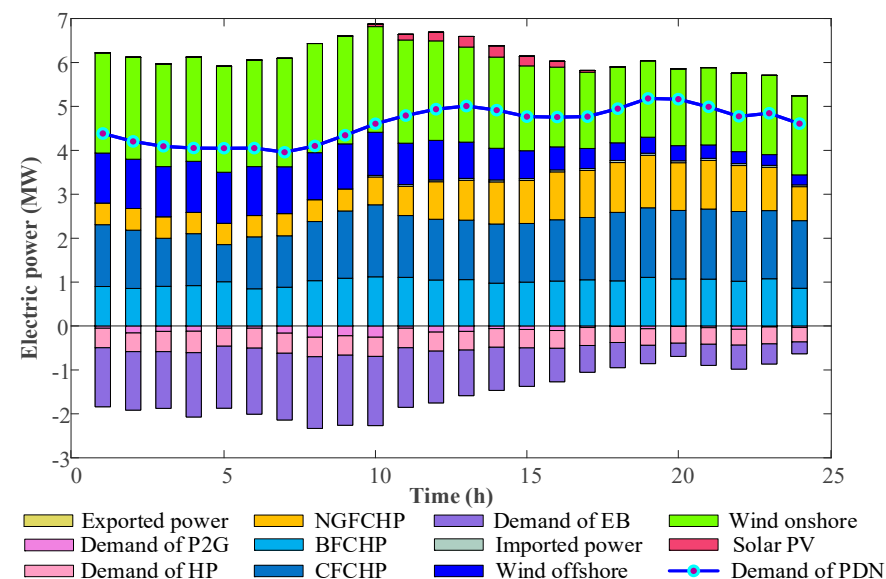


Figure 8. Optimal schedule of PDN in the day-ahead stage.

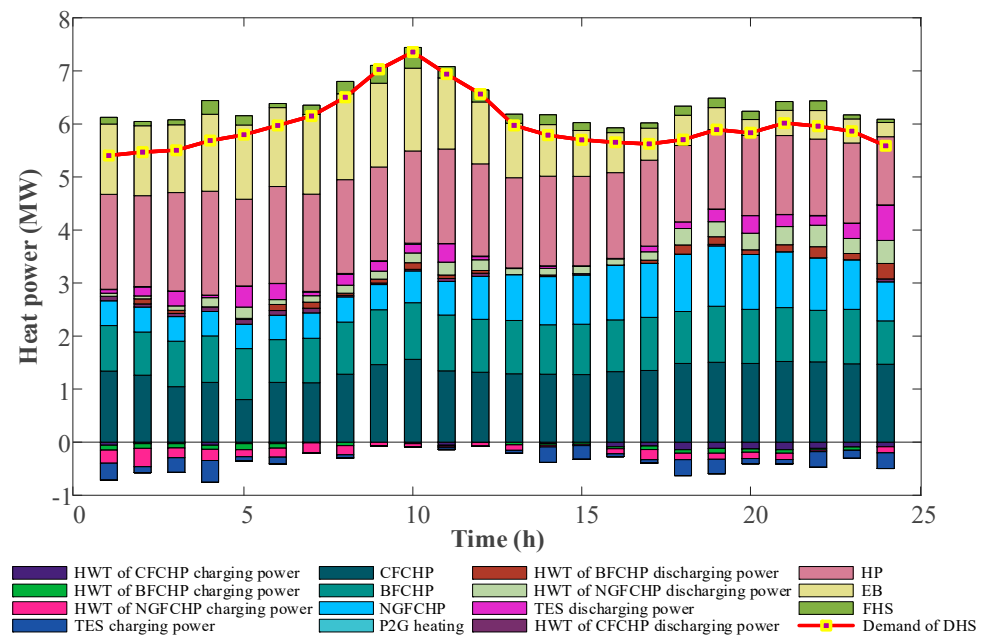


Figure 9. Optimal schedule of DHN in the day-ahead stage.

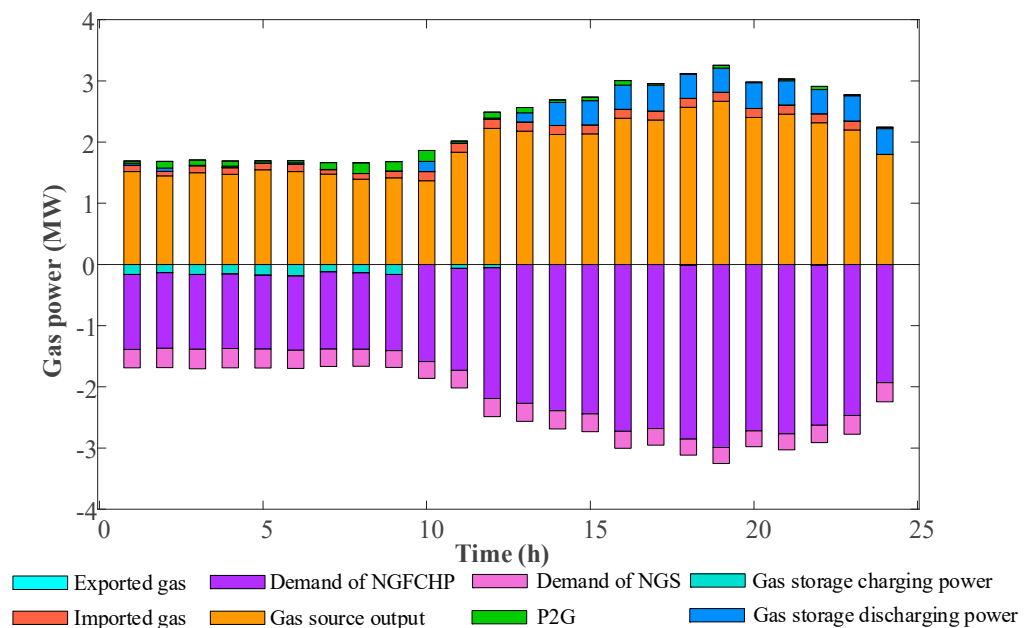


Figure 10. Optimal schedule of NGS in the day-ahead stage.

As discussed above, the CIES can achieve the supply and demand balance between electricity, gas and heat. In fact, it is paramount to jointly consider the multiple factors such as energy prices, load characteristics, energy network working conditions while crafting a scheduling scheme for CIES. Particularly, energy network working conditions of multipipe systems is relatively important for further applications to actual complicated systems. According to Figures 11 and 12, the proposed dispatching strategy for CIES can solve the overall operation strategies of energy networks and the detailed energy supply strategies on the premise of ensuring that the NGS nodal natural gas pressure and flow rate satisfy network working conditions.

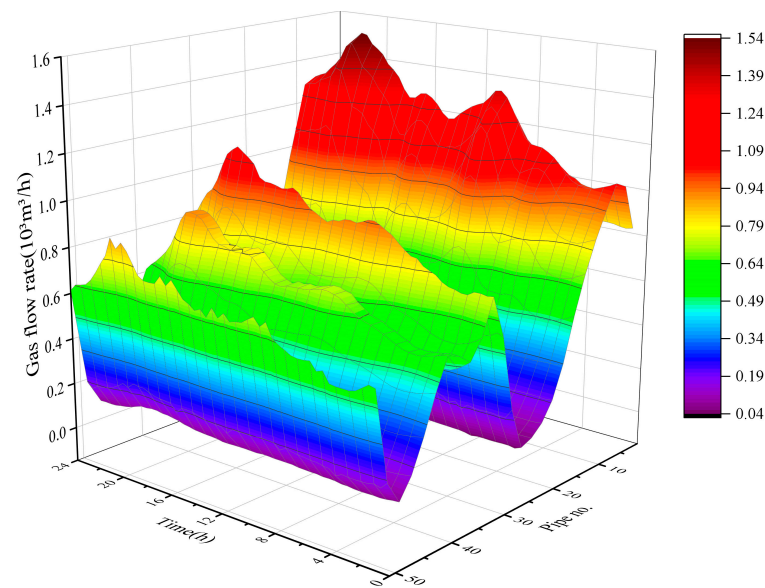


Figure 11. Gas flow rate in the NGS pipelines.

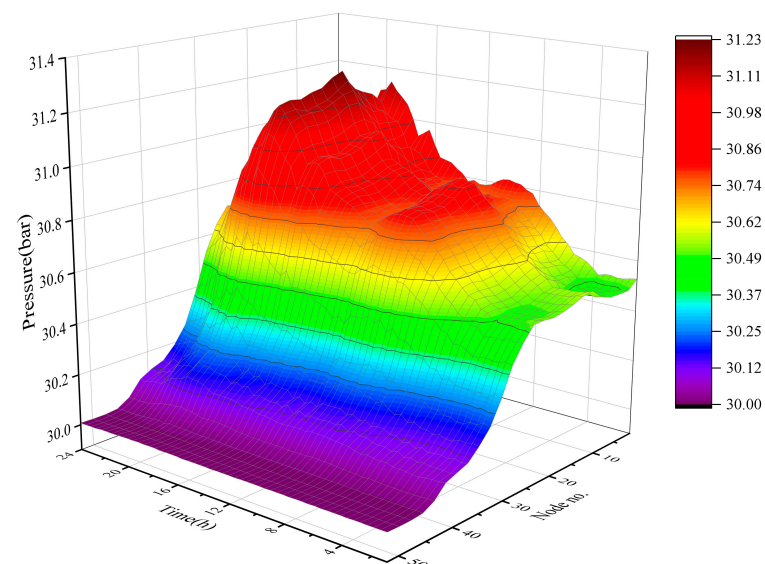


Figure 12. Pressure distribution of the NGS nodes.

4.3. Real-Time Scheduling Analysis

In the real-time scheduling stage, based on the day-ahead scheduling results, the CIES can change its operation status through the flexible and rapid responses of fast units, to compensate for the fluctuations of load demand and renewable energy. The real-time scheduling must have the ability to acquire the optimal control action within a reasonable time. Thus, it is essential to select a reasonable prediction horizon based on the desired computation time and storage capacity of the system. Besides, the penalty for deviation from pre-scheduled values obtained by day-ahead scheduling should be fully considered to minimize the entire operation cost under the condition of meeting the stability of the system. Based on these considerations, the real-time optimal dispatching results obtained by the case calculation are shown in Figure 13, Figure 14, and Figure 15, respectively.

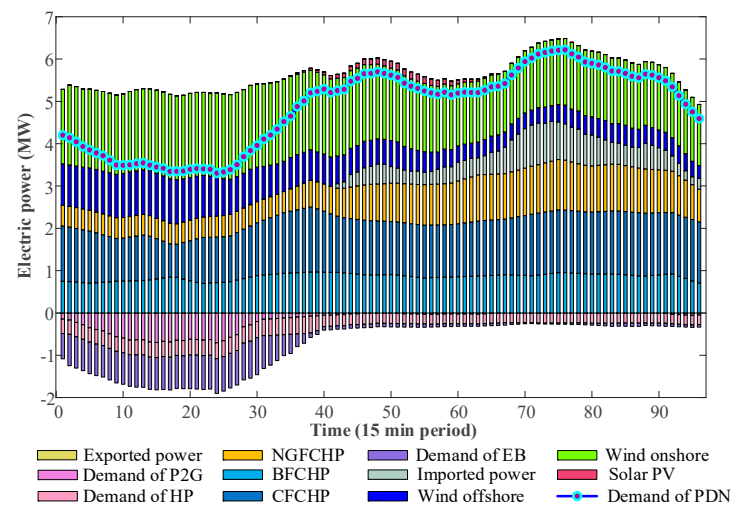


Figure 13. Optimal schedule of PDN in the real-time stage.

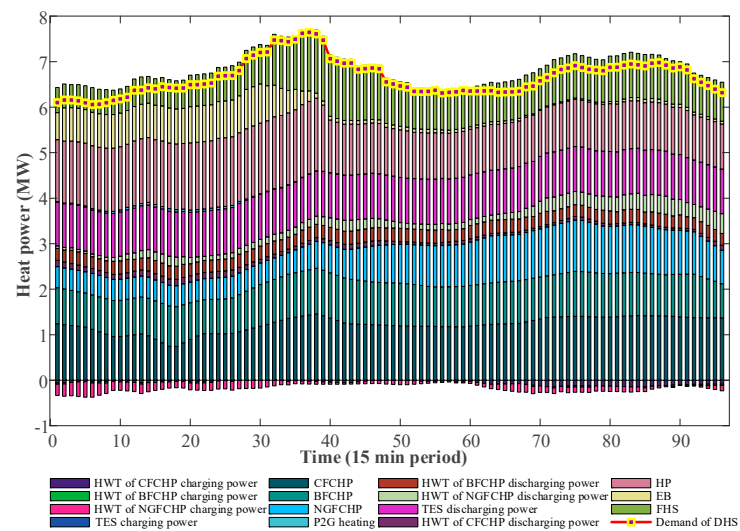


Figure 14. Optimal schedule of DHN in the real-time stage.

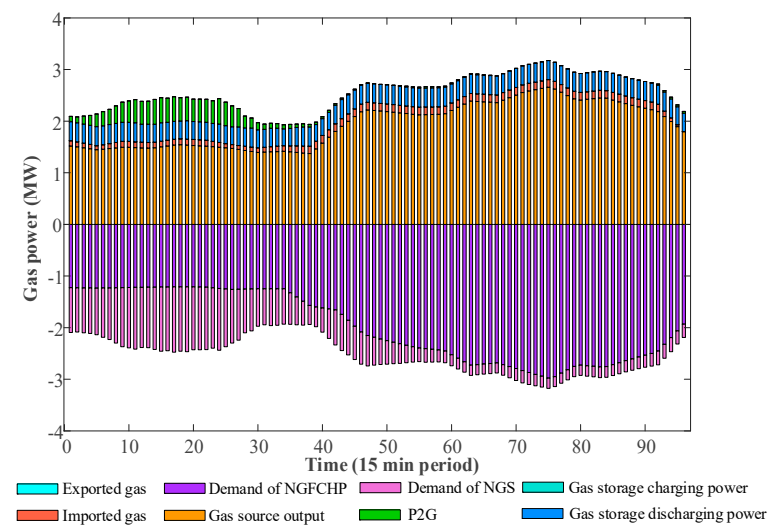


Figure 15. Optimal schedule of NGS in the real-time stage.

It is seen that the proposed strategy can accomplish a multi-energy supply and demand balance in the RT scheduling, while some differences exist in the scheduling schemes of RT and DA stages. From Figure 13, it can be observed that EB and P2G units are mainly dispatched from period 0 to period 37 due to low-price electrical energy, while heat pumps are operated during the whole day as a proven and high-efficient technology. The insufficient part in the RT stage is supplemented by imported power during peak hours.

As for the DHN, both the thermal energy purchased from FHS and the discharging power of TES and HWT have gained compared to the DA scheduling in the RT scheduling stage, as shown in Figure 14. This is because RT scheduling allows for more accurate forecasting of heat demand and supply, enabling better optimization of heat purchase and storage. Additionally, RT scheduling may provide more flexibility by considering thermal inertia in response to unexpected changes in heat demand or supply, which can result in higher utilization of both heat purchase and storage systems.

In the NGS, the increment of imported gas and GST discharging power can ensure reliable gas system operations during RT scheduling. However, the increased volatility of gas load during real-time scheduling may be a concern, as it can lead to greater instability in the gas network and potentially result in additional cost and environmental impacts. To address this issue, the usage of gas linepack is an effective method to provide flexibility to manage fluctuations in gas demand and supply.

The CIES obtains more flexibility due to the presence of P2G units. In Figure 16, at the peak period of the wind power in the early morning, P2G units play a critical role in reducing wind power curtailment and providing upward flexibility for NGS by consuming the surplus wind power as much as possible to generate heat and gas. In the period of low wind power, since most of the wind power has been completely consumed, it is needless to dispatch the high cost P2G and the downward flexibility is mainly provided.

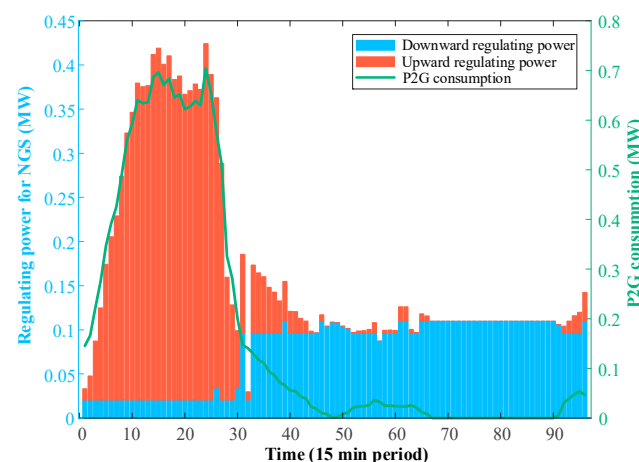


Figure 16. Flexibility provided by P2G units and its electricity consumption.

Figure 17 depicts the values of gas flow rate in the natural gas network pipelines. Compared to the DA scheduling stage, the gas flow in the pipeline exhibits greater instability and complexity during the RT scheduling stage, because RT scheduling requires a rapid response to the changes in gas flow in the pipeline to maintain the stable operation of the pipeline. In addition, the hot water temperature of supply nodes and return nodes are illustrated in Figure A1. During the peak heating demand, which usually occurs in winter or cold days, the hot water temperature of the supply side is increased and maintained at a high level to ensure sufficient heat transfer to the buildings or zones, while the hot water temperature of the return side drops due to the higher heat utilization rate at peak demand.

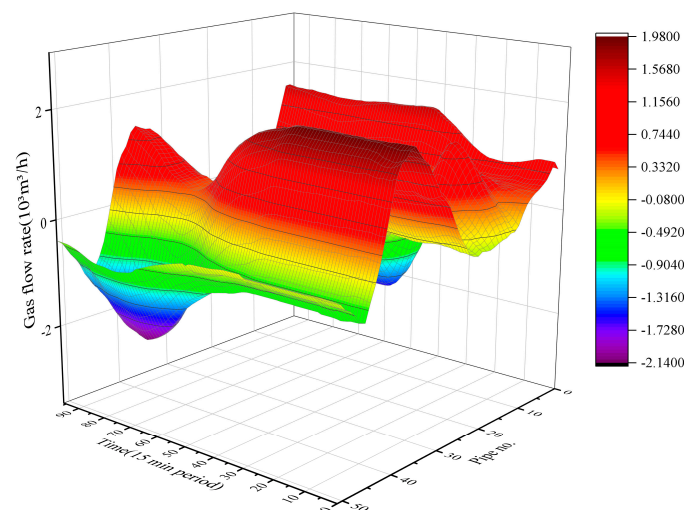


Figure 17. Gas flow rate in the NGS pipelines during the RT scheduling stage.

4.4. The Impacts of Thermal Inertial and Gas Linepack

The combination of building thermal inertia and gas linepack can contribute to greater energy efficiency and cost savings, which has significant impacts on the performance and sustainability of CIES.

As expected, different types of buildings exhibit different flexibility characteristics in reducing energy consumption at durations when the total load is at peak values. The results are also studied to better understand how daily thermal flexibility profiles vary with building types. The resulting HVAC power consumptions are depicted in Figure 18 as they represent three different levels of building thermal mass. Commercial and residential buildings have smaller thermal mass compared to industrial plants and therefore show faster thermal dynamics than industrial plants. This is a key reason why the large industrial plant is more flexible in increasing energy consumption than in decreasing it.

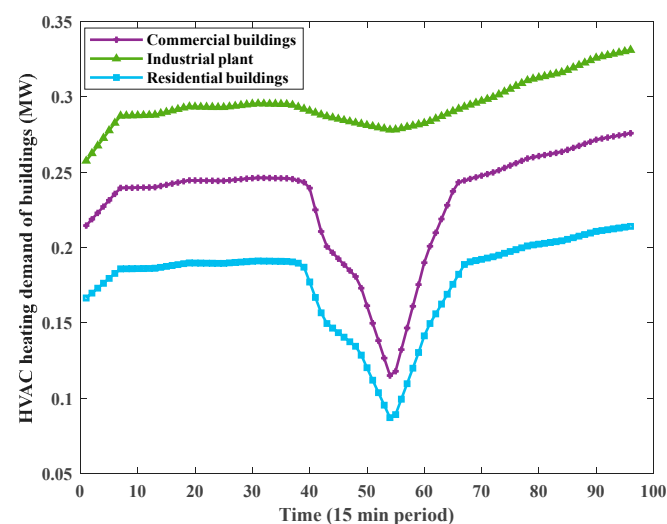


Figure 18. HVAC heating demand of different building types.

As shown in Figure 19, commercial buildings and residential buildings with small areas can be heated up fast and therefore their temperature setpoints are higher than those of industrial plants. As for industrial plants, the envelope structure is quite different from that of residential and commercial buildings, resulting in greater thermal inertia, so the space heating and heat dissipation of industrial plants are relatively slow. In addition,

the heatmaps in Figure 19 also show that the zone temperatures of buildings are well-maintained within the required range.

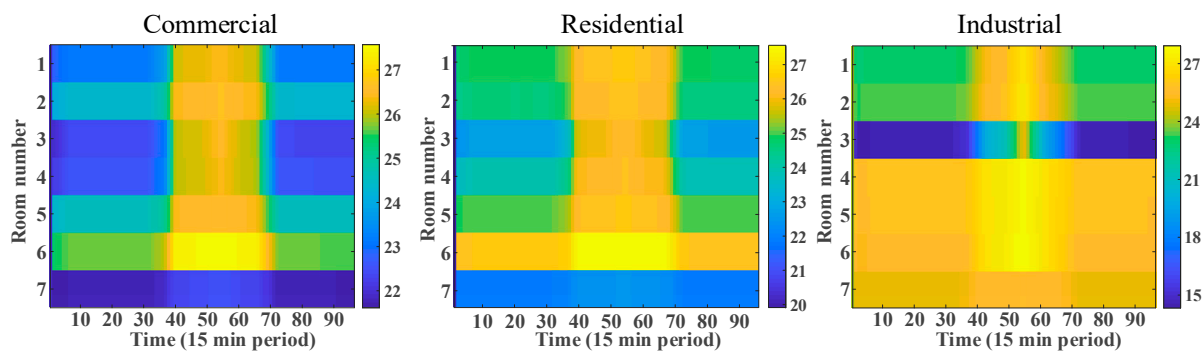


Figure 19. Heatmaps of zone temperatures in different building types.

Gas linepack can serve as a buffer to mitigate supply and demand imbalances, thereby providing a possibility to stabilize fluctuations in NGS. Additionally, due to the slower dynamics of gas flow, part of the gas load can be supplied by the gas linepack. Figure 20 illustrates the linepack storage dynamics of each NGS pipeline during RT scheduling. As can be observed, the linepack increases with the decrease of gas load, such as period 0 to 20 and period 50 to 60. By contrast, the linepack releases gradually due to the increase of gas load at peak hours (period 20 to 40). It reflects the buffering characteristics of the linepack, which can reduce pipeline congestion and improve the flexibility.

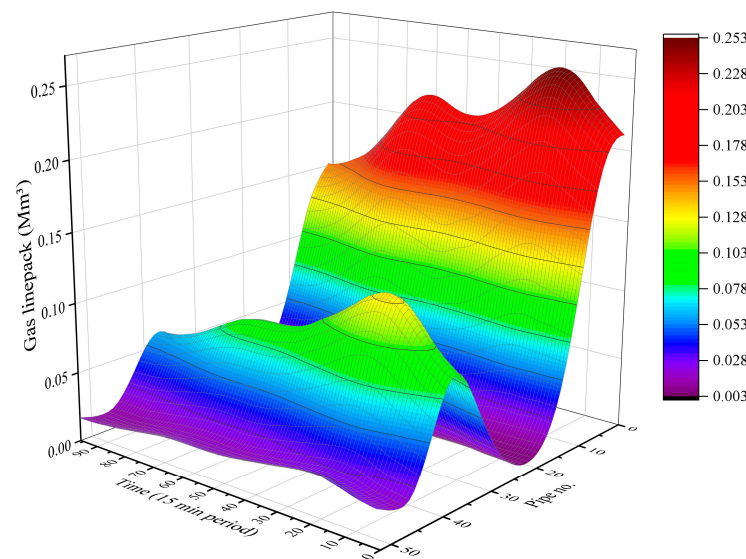


Figure 20. Storage level of linepack in the NGS pipelines.

By incorporating building thermal inertia and gas linepack into the real-time scheduling of CIES, operators can better optimize the energy efficiency and economic performance of the scheduling scheme. The system cost and computation complexity for each scheduling period during RT scheduling are both analysed in Figure 21. It suggests that considering building thermal inertia and gas linepack in an IES can result in lower total operational cost. However, the extent of the cost reduction depends on the system's overall load level. During periods of low overall load from period 0 to period 45, considering system inertia may contribute to higher operational cost as the benefits of building thermal inertia and gas linepack are less pronounced when the system is not heavily utilized. On the other hand, during periods of peak demand, the incorporation of system inertia can significantly reduce operational cost. This is because building thermal inertia and gas linepack can

effectively balance energy supply and demand during peak periods, thereby reducing the need for expensive and inefficient peak energy generation. Besides, the computation time for each scheduling period consistently falls within the range of 265 to 285 s, which is in line with the time interval of the RT scheduling stage.

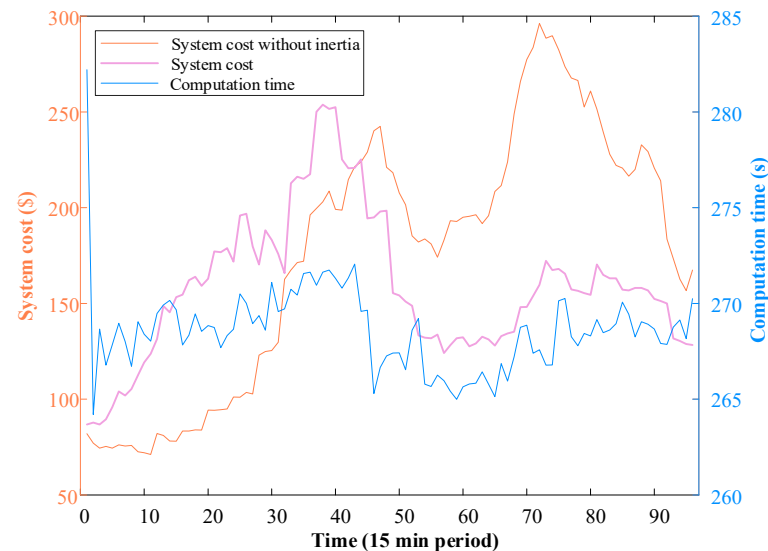


Figure 21. Storage level of linepack in the NGS pipelines.

Table 4 summarizes the total operational cost for different cases. It implies that, compared with the day-ahead stage, the total operational cost of the real-time scheduling stages is much lower. This is mainly because the system uncertainties, including offshore and onshore wind farm generation, solar PV output and electric demand, will gradually decline with a diminishing time resolution, thus decreasing the difference between the scheduling strategy and the actual operation situation of the CIES. Based on fully utilizing thermal inertia and gas linepack during RT scheduling, the operational economy could be further improved by 9.6% compared to the ignorance of system inertia components. Therefore, it is essential to consider system inertia to ensure the long-term sustainability and cost-effectiveness of energy systems.

Table 4. Total operational cost for different cases.

Scheduling Stage	System Inertia	Total Operational Cost (\$)
Day-ahead	×	19,784
Day-ahead	✓	17,561
Real-time	×	16,855
Real-time	✓	15,237

5. Conclusions

In this study, an SMPC-based multi-temporal-spatial-scale flexibility scheduling strategy is introduced for the CIES considering multiple uncertainty sources and system inertia components. To cope with the system uncertainties, the auto-regressive model and scenario generation method are embedded in the SMPC-based framework. The inclusion of scheduling at multiple time scales encompassing DA and RT scheduling schemes, and in terms of multiple spatial scales, the comprehensive and holistic analysis of the entire CIES and the detailed analysis of typical building within different communities, have made significant contributions towards optimizing CIES operation. The validity of the proposed model and method has been confirmed through a series of case studies, leading to the following conclusions:

1. After applying the proposed scheduling method, the CIES can better counteract operational uncertainties and promote energy supply and demand balance at multi-temporal-spatial-scale. More specifically, the proposed SMPC-based framework integrates the measured and forecasted data of uncertainty sources to represent future uncertainty by means of the auto-regressive model and scenario generation method, furnishing valuable information for the expected uncertainty bounds over the system demand and RES generation. Intuitively, the significant improvement of prediction accuracy lays a solid foundation for the scheduling schemes.

2. The DA and RT scheduling results demonstrate the feasibility of the proposed strategy in maintaining a supply and demand balance between electricity, gas and heat energy at multiple temporal scales, as well as satisfying energy network working conditions of multipipe systems. Moreover, the integration of SMPC-based RT scheduling into the energy system can lead to a considerable reduction in total operational cost compared to the DA scheduling.

3. In addition to analysing the holistic scheduling of CIES, detailed analysis of the thermal inertia characteristics of buildings in different communities at multiple spatial scales is also imperative. The analysis reveals that small buildings in residential and commercial communities can provide more flexibility resources with faster response time for the energy system, while large buildings in industrial community have large thermal mass and therefore slower thermal dynamics and greater thermal inertia due to predominant differences in building envelopes from those in residential and commercial communities, making it difficult to respond to flexibility demands quickly.

The work of this paper still has certain limitations. For instance, the PDN model utilizes a DC power flow model, considering only the demand-side thermal inertia of the DHN and neglecting the network-side thermal inertia, load forecasting for the DHN and NGS has not been implemented. In future research, the foundational model of the CIES will be refined for improved alignment with real-world scenarios. Besides, the integration of hydrogen will be explored as a clean and efficient energy source to accommodate surplus renewable energy.

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Nomenclature

CIES	community integrated energy system	CFP	coal fired plant
SMPC	stochastic model predictive control	HWT	hot water tank
RES	renewable energy sources	TES	thermal energy storage
IDR	integrated demand response	FHS	flexible heat supplier
DA	day-ahead	HP	heat pump
RT	real-time	MILP	mixed-integer linear programming
DHN	district heating network	EB	electric boiler
NGS	natural gas system	HSU	heat storage unit
PDN	power distribution network	GST	gas storage tank
P2G	power to gas	BFP	biomass fired plant
CHP	combined heat and power	GFP	gas fired plant
HVAC	heating, ventilation, and air-conditioning	ECDF	empirical cumulative distribution function

Appendix A

Table A1. Detailed parameters of CIES.

NO.	CHP (kW)	EB (MW)	HP (MW)	COP of HP	P2G (MW)
1	525	0.32	0.008	3.985	0.163
2	120	0.14	0.001	3	0.276
3	450	0.28	0.021	4.15	0.163
4	52	0.04	0.033	4	0.049
5	73	0.40	0.001	5.8	0.276
6	392	0.06	0.021	4.875	0.134
7	120	0.14	0.009	4.3	0.049
8	392	0.10	0.021	3.6	0.163
9	120	0.09	0.033	3.985	0.276
10	120	0.02	0.064	3	0.292
11	392	0.08	0.001	4.15	0.049
12	350	0.10	0.012	4	0.292
13	392	0.10	0.008	5.8	0.276
14	120	0.09	0.001	4.875	0.276
15	73	0.02	0.021	4.3	0.163
16	73	0.08	0.033	3.6	0.049
17	73	0.10	0.001	3.985	0.049
18	120	0.10	0.009	3	0.163
19	73	0.09	0.033	4.15	0.292
20	392	0.02	0.064	4	0.276
21	120	0.08	0.012	5.8	0.163
22	392	0.10	0.033	4.875	0.276
23	392	0.32	0.001	4.3	0.049
24	392	0.14	0.021	3.6	0.292
25	392	0.28	0.009	3.985	0.163
26	120	0.04	0.021	3	0.049
27	120	0.40	0.033	4.15	0.276
28	450	0.06	0.064	4	0.292
29	377	0.14	0.001	5.8	0.163
30	52	0.10	0.012	4.875	0.049
31	407	0.09	0.001	4.3	0.292
32	377	0.02	0.009	3.6	0.163
33	407	0.08	0.033	4.3	0.276

Appendix B

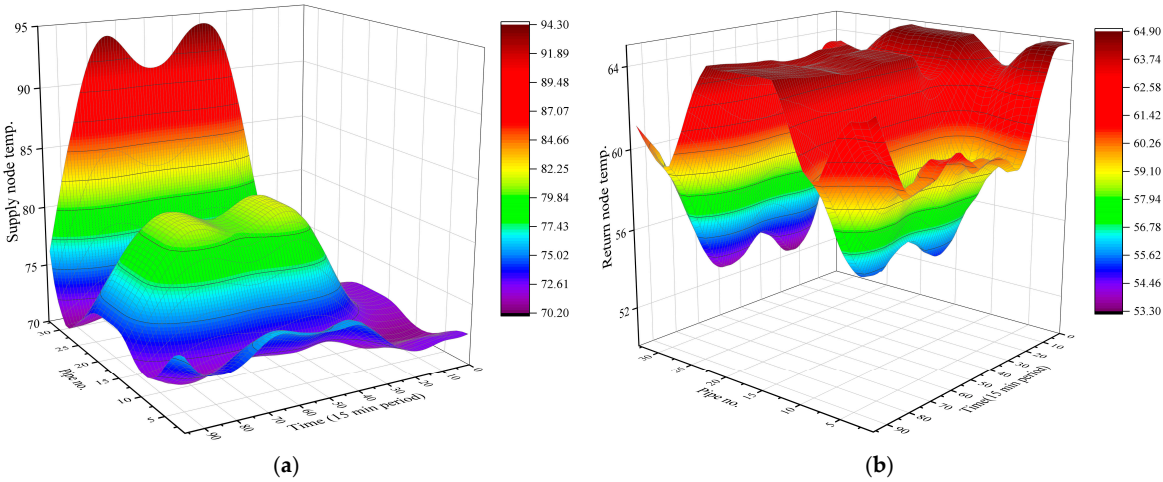


Figure A1. Nodal temperatures in the DHN for supply side (a) and return side (b).

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