Co-optimization Model for Scheduling of Prosumers in Joint Local Energy and Flexibility Markets

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***Abstract*—In modern power systems with growing penetration of distributed energy resources (DERs), prosumers can actively participate in local energy and flexibility markets by optimally scheduling their DER portfolios, thereby supporting grid operation while enhancing their economic benefits. However, existing studies have often overlooked the complexities of participating in joint local energy and flexibility markets, leaving a portion of the potential economic benefit unrealized. This paper proposes a co-optimization framework for the coordinated scheduling of a prosumer, comprising multiple DER types, to enable such participation. The model is implemented via a model predictive control (MPC) approach to minimize the total operational cost, including energy purchases and sales, as well as revenues from providing upward and downward flexibility services, subject to joint energy-flexibility provision constraints. Simulation results show that the proposed coordinated scheduling approach reduces operational costs by approximately 25% compared to a sequential scheduling strategy.**

***Index Terms*—Prosumers, distributed energy resources, joint energy and flexibility markets, coordinated scheduling problem.**

NOMENCLATURE

A. Symbols and Indices

el, th	Electrical and thermal energy
s, b	Electricity sold to and bought from the grid
d	Load demand
e, f	Energy and flexibility markets
up, dn	Upward and downward flexibility
ch, dis	Charging and discharging
pv, bs, ev	Photovoltaic, battery storage, electric vehicle
hp, ts	Heat pump, thermal storage
av, rtd	Available power and rated power
ini, des	Initial SoC and desired SoC
$\overline{(\cdot)}, \underline{(\cdot)}$	Maximum and minimum allowable levels

B. Parameters and Variables

λ	Price of energy or flexibility markets
p	Electrical or thermal power
α	Enabled flexibility factor
ψ	Binary variable showing charge/discharge status
SoC	SoC level of storage devices
η	Efficiency parameter
E	Energy capacity of storage devices
ΔT	Duration of a time interval

I. INTRODUCTION

Despite their numerous benefits, the accelerated penetration of intermittent distributed energy resources (DERs), such as photovoltaic (PV) panels and electric vehicles (EVs), has raised operational challenges for distribution systems. These challenges primarily include voltage fluctuations and imbalances, grid overloading, and power quality issues [1]. For instance, the study conducted on two real Australian grids in [2] demonstrates that when EV hosting capacity exceeds 40% in urban and 20% in rural networks, technical issues such as transformer overloading and voltage limit violations occur. To address these challenges, distribution system operators (DSOs) utilize demand-side flexibility provided by DERs through smart energy management strategies. In this context, transactive energy (TE) has introduced as a promising solution, enabling prosumers–agents who both consume and produce energy–to optimally schedule their flexible resources by trading energy and flexibility through local market platforms [3].

Local energy and flexibility markets (LEM and LFM) are well-established TE mechanisms in the literature. An LEM facilitates energy trading among prosumers, aiming to maximize local energy consumption and enable participants to manage their surplus and deficit in a market environment. In contrast, an LFM enables system operators to dispatch available flexibility declared by prosumers in a market-based manner to address operational security issues such as voltage violations and network congestion, extending traditional concept of ancillary services to the distribution level [4]. Among the different LFM designs, upward and downward flexibility markets are the most prevalent. Upward flexibility refers to the capability of a prosumer to increase its net power injection into the grid (by increasing generation or reducing consumption) in response to supply deficit. Conversely, downward flexibility denotes the ability to decrease net power injection by reducing generation or increasing consumption) to accommodate surplus generation or relieve grid constraints [5]. Together, these energy and flexibility markets create financial incentives for prosumers to optimally schedule their DER portfolios while supporting secure and efficient distribution system operation.

In the literature, several studies have explored mechanisms to enable prosumer participation in LEMs and LFMs, as well as strategies for optimal participation in these markets. In particular, the works in [6]–[8] develop LEM mechanisms to enable the active participation of specific flexible resources–heat pumps (HPs), EVs, and battery storage systems (BSSs), respectively–while accounting for user-specific constraints and

real-time grid conditions. A TE framework is presented in [9] that allows the DSO to utilize the flexibility of residential buildings in LFMs to alleviate transformer overloading. The authors in [10] propose an LFM that enables residential customers to optimize their flexibility schedules based on predefined requirements. Yet, these studies focus on either LEMs or LFMs and do not address their integrated operation.

To address this limitation, some studies have proposed LFM mechanisms alongside LEMs to enable prosumers to participate in both markets and derive economic benefits from each; however, such participation is typically modeled in a sequential manner. For instance, the authors in [11] propose a framework where prosumers first participate in peer-to-peer (P2P) LEM, after which the required flexibility is determined by the DSO and procured through a separate LFM. In [12], the maximum available upward and downward flexibility is determined based on the optimal scheduling of prosumers in the LEM and subsequently offered in the flexibility market. The LEM and LFM models presented in [13] enable aggregators to participate in both day-ahead energy and local flexibility markets, where energy commitments are determined first and flexibility is subsequently allocated to satisfy grid constraint at the point of common coupling.

Although sequential approaches may offer certain benefits for prosumers, the coupling between energy trading and flexibility provision–captured through the joint energy-flexibility constraints–necessitates the simultaneous optimization of prosumers' participation in both markets. For example, [14] proposes a joint optimization framework for a utility-scale BSS to participate in the energy and ancillary service markets of the Australian National Electricity Market (NEM). While the study focuses on wholesale markets, the model is conceptually extendable to local markets; however, similar to many other studies, it considers only a single flexible resource, leaving coordinated scheduling of prosumers with multiple DER types largely unaddressed.

Motivated by the aforementioned limitations, this paper proposes an optimization framework for the coordinated scheduling of prosumers participating in joint local energy and flexibility markets. The prosumer is equipped with multiple types of DERs, including PV system, BSS, EV charger, thermal storage system (TSS), and heat pump (HP). The proposed framework is formulated as a mixed-integer linear programming (MILP) problem and implemented via a model predictive control (MPC) approach. This model enables the prosumer to minimize its total operational cost through optimal energy trading and upward and downward flexibility provision. The optimization is subject to electrical and thermal energy balance constraints, along with the operational constraints of each DER, including technical limits, user-specific requirements, and the coupling between energy scheduling and flexibility provision. Finally, we compare the total operational cost in the proposed framework with that of a sequential scheduling approach, in which the prosumer first optimizes its participation in the LEM and subsequently offers the available flexibility in LFMs, to quantify the resulting cost saving.

The rest of this paper is organized as follows. Section II presents the problem formulation, Section III provides the results and discussion, and Section IV concludes the paper.

II. Problem Formulation

This section presents the optimization problem for the coordinated scheduling of a prosumer participating in joint local energy and flexibility markets. The design of these markets is not the focus of this work; instead, the market operation is represented through exogenous market clearing prices. In particular, the local market environment is operated such that the dispatch of energy and upward and downward flexibility services is co-optimized to ensure supply-demand balance and system security. The prosumer is considered a price taker, accepting the market clearing price without attempting to influence it. The activation of flexibility is not explicitly modeled, and revenue from the LEM is determined by energy traded, while revenue from LFMs is based on the enabled upward and downward capacity, regardless of whether this flexibility is actually activated. Accordingly, the objective function is formulated as follows.

$$\text{Minimize } \ obj = \sum_{t \in T} \mathcal{OC}_t \tag{1}$$

$$\begin{aligned}\mathcal{OC}_t = \big[&\big(\lambda_t^{e,b}\, p_t^{e,b} - \lambda_t^{e,s}\, p_t^{e,s}\big) - \\ &\big(\alpha_t^{f,up}\lambda_t^{f,up}\, p_t^{f,up} + \alpha_t^{f,dn}\lambda_t^{f,dn}\, p_t^{f,dn}\big)\big]\,\Delta t\end{aligned} \tag{2}$$

The first and second terms in (2) represent the cost and revenue of energy purchase and sale, respectively, while the third and fourth terms correspond to the revenue from upward and downward flexibility services. It is worth noting that the prices for selling and purchasing energy differ due to the distinct marginal loss factors of the seller and buyer agents.

A. Energy Market Operational Constraints

The optimal scheduling of the prosumer, comprising various energy assets, in the local energy market is subject to several constraints, including electrical and thermal energy balance, PV generation limits, BSS and TSS scheduling, EV charging, and HP operation, as detailed below.

$$\begin{aligned}p_t^{e,b} - p_t^{e,s} =& p_t^{el,d} - p_t^{pv} + (p_t^{bs,ch} - p_t^{bs,dch}) + p_t^{ev,ch} \\ &+ (p_t^{hs,elz} - p_t^{hs,fc}) + p_t^{el,hp}\end{aligned} \tag{3}$$

$$p_t^{th,d} = p_t^{th,hp} + (p_t^{ts,dch} - p_t^{ts,ch}) \tag{4}$$

$$p_t^{pv} \le p_t^{pv,av} \tag{5}$$

$$0 \le p_t^{bs,ch} \le p^{bs,rtd}\psi_t^{bs} \tag{6}$$

$$0 \le p_t^{bs,dch} \le p^{bs,rtd}(1 - \psi_t^{bs}) \tag{7}$$

$$SoC_{t+1}^{bs} = SoC_t^{bs} + \frac{\big(p_t^{bs,ch}\,\eta^{bs,ch} - p_t^{bs,dch}/\eta^{bs,dch}\big)\Delta t}{E^{bs}} \tag{8}$$

$$SoC_t^{bs} = SoC^{bs,ini}, \ \ \forall t \in \{1\} \tag{9}$$

$$\underline{SoC}^{bs} \le SoC_t^{bs} \le \overline{SoC}^{bs} \tag{10}$$

$$0 \le p_t^{ev,ch} \le p^{ev,rtd}, \ \ \forall t \in [AT, DT] \tag{11}$$

$$SoC_{t+1}^{ev} = SoC_t^{ev} + \frac{p_t^{ev,ch}\,\eta^{ev}\,\Delta t}{E^{ev}}, \quad \forall t \in [AT, DT] \tag{12}$$

$$SoC_t^{ev} = SoC^{ev,ini} \quad \forall t \in \{AT\} \tag{13}$$

$$SoC_t^{ev} \geq SoC^{ev,des}, \quad \forall t \in \{DT\} \tag{14}$$

$$\underline{SoC}^{ev} \leq SoC_t^{ev} \leq \overline{SoC}^{ev}, \quad \forall t \in [AT, DT] \tag{15}$$

$$p_t^{th,hp} = CoP^{hp} p_t^{el,hp} \tag{16}$$

$$0 \leq p_t^{el,hp} \leq p^{hp,rtd} \tag{17}$$

$$0 \leq p_t^{ts,ch} \leq p^{ts,rtd} \psi_t^{ts} \tag{18}$$

$$0 \leq p_t^{ts,dch} \leq p^{ts,rtd}(1 - \psi_t^{ts}) \tag{19}$$

$$SoC_{t+1}^{ts} = SoC_t^{ts} + \frac{\left(p_t^{ts,ch}\,\eta^{ts,ch} - p_t^{ts,dch}/\eta^{ts,dch}\right)\Delta t}{E^{ts}} \tag{20}$$

$$SoC_t^{ts} = SoC^{ts,ini}, \quad \forall t \in \{1\} \tag{21}$$

$$\underline{SoC}^{ts} \leq SoC_t^{ts} \leq \overline{SoC}^{ts} \tag{22}$$

The electrical energy balance constraint (3) ensures that the net electricity exchanged with the grid satisfies the prosumer's electrical demand, considering PV generation, BSS scheduling, EV charging, and the electricity consumption of the HP. Similarly, the thermal energy balance constraint (4) ensures that thermal demand is met through the coordinated operation of the HP and TSS. Regarding DER operational constraints, equation (5) limits the PV generation to its available power. Equations (6)-(10) describe the BSS operation, including charging and discharging power limits, the temporal energy balance as captured by the state of charge (SoC) dynamics, and the initial and allowable SoC levels. Equations (11)-(15) represent the EV charging process during the plugged-in period, constrained by charging limits, the initial and desired SoC at arrival and departure times, the temporal energy balance in vehicle battery, and allowable SoC bounds. Equations (16) and (17) link the thermal output of the HP to its electrical input through the coefficient of performance (CoP) and limit its electrical consumption. Finally, equations (18)-(22) describe the operation of the TSS, which is analogous to the BSS but for thermal power instead of electrical power.

B. Flexibility Market Operational Constraints

In addition to the operational constraints governing the optimal scheduling of the prosumer in the LEM, participation in the joint LFM introduces additional constraints. These constraints capture the coupling between DER scheduling and the provision of flexibility services, as detailed below.

$$p_t^{f,dn} = p_t^{f,dn,pv} + p_t^{f,dn,bs} + p_t^{f,dn,ev} + p_t^{f,dn,hs} + p_t^{f,dn,hp} \tag{23}$$

$$p_t^{f,up} = p_t^{f,up,pv} + p_t^{f,up,bs} + p_t^{f,up,ev} + p_t^{f,up,hs} + p_t^{f,up,hp} \tag{24}$$

$$p_t^{pv} - p_t^{f,dn,pv} \geq 0 \tag{25}$$

$$p_t^{pv} + p_t^{f,up,pv} \leq p_t^{pv,av} \tag{26}$$

$$p_t^{bs,ch} - p_t^{bs,dch} + p_t^{f,dn,bs} \leq p^{bs,rtd} \tag{27}$$

$$p_t^{bs,ch} - p_t^{bs,dch} + p_t^{f,dn,bs} \leq \frac{(\overline{SoC}^{bs} - SoC_t^{bs})E^{bs}}{\eta^{bs,ch}\Delta t} \tag{28}$$

$$p_t^{bs,dch} - p_t^{bs,ch} + p_t^{f,up,bs} \leq p^{bs,rtd} \tag{29}$$

$$p_t^{bs,dch} - p_t^{bs,ch} + p_t^{f,up,bs} \leq \frac{(SoC_t^{bs} - \underline{SoC}^{bs})E^{bs}\eta^{bs,dch}}{\Delta t} \tag{30}$$

$$p_t^{ev,ch} + p_t^{f,dn,ev} \leq p^{ev,rtd} \tag{31}$$

$$p_t^{ev,ch} + p_t^{f,dn,ev} \leq \frac{(\overline{SoC}^{ev} - SoC_t^{ev})E^{ev}}{\eta^{ev}\Delta t} \tag{32}$$

$$p_t^{ev,ch} - p_t^{f,up,ev} \geq 0, \quad \text{if } AT_t > RT_t \tag{33}$$

$$p_t^{f,up,ev} \leq \frac{(AT_t - RT_t)p^{ev,rtd}}{\Delta t}, \quad \text{if } AT_t > RT_t \tag{34}$$

$$AT_t = DT - t \tag{35}$$

$$RT_t = \frac{(SoC^{ev,des} - SoC_t^{ev})E^{ev}}{\eta^{ev}p^{ev,rtd}} \tag{36}$$

$$p_t^{f,up,ev} = 0, \quad \text{if } AT_t \leq RT_t, \tag{37}$$

$$p_t^{el,hp} + p_t^{f,dn,hp} \leq p^{hp,rtd} \tag{38}$$

$$p_t^{el,hp} - p_t^{f,up,hp} \geq 0 \tag{39}$$

$$p_t^{th,dn,hp} = CoP^{hp}(p_t^{el,hp} + p_t^{f,dn,hp}) \tag{40}$$

$$p_t^{th,up,hp} = CoP^{hp}(p_t^{el,hp} - p_t^{f,up,hp}) \tag{41}$$

$$p_t^{th,d} = p_t^{th,dn,hp} + (p_t^{dn,ts,dch} - p_t^{dn,ts,ch}) \tag{42}$$

$$p_t^{th,d} = p_t^{th,up,hp} + (p_t^{up,ts,dch} - p_t^{up,ts,ch}) \tag{43}$$

$$0 \leq p_t^{dn,ts,ch} \leq p^{ts,rtd}\psi_t^{dn,ts} \tag{44}$$

$$p_t^{dn,ts,ch} \leq \frac{(\overline{SoC}^{ts} - SoC_t^{ts})E^{ts}}{\eta^{ts,ch}\Delta t} \tag{45}$$

$$0 \leq p_t^{dn,ts,dch} \leq p^{ts,rtd}(1 - \psi_t^{dn,ts}) \tag{46}$$

$$p_t^{dn,ts,dch} \leq \frac{(SoC_t^{ts} - \underline{SoC}^{ts})E^{ts}\eta^{ts,dch}}{\Delta t} \tag{47}$$

$$0 \leq p_t^{up,ts,ch} \leq p^{ts,rtd}\psi_t^{up,ts} \tag{48}$$

$$p_t^{up,ts,ch} \leq \frac{(\overline{SoC}^{ts} - SoC_t^{ts})E^{ts}}{\eta^{ts,ch}\Delta t} \tag{49}$$

$$0 \leq p_t^{up,ts,dch} \leq p^{ts,rtd} \cdot \left(1 - \psi_t^{up,ts}\right) \tag{50}$$

$$p_t^{up,ts,dch} \leq \frac{(SoC_t^{ts} - \underline{SoC}^{ts})E^{ts}\eta^{ts,dch}}{\Delta t} \tag{51}$$

The total available downward and upward flexibility at each timestep, aggregating contributions from all relevant energy assets, is represented by equations (23) and (24), respectively. The coupling between DER scheduling and the provision of upward and downward flexibility is captured by the constraints described below. For the PV system, equations (25) and (26) ensure that downward flexibility does not exceed scheduled generation, while upward flexibility is limited by the available PV generation. The BSS provides downward and upward flexibility as defined by constraints (27)-(30). Downward flexibility increases net consumption by adjusting charging and discharging powers, limited by the rated power and the upper SoC bound as defined in (27) and (28), while upward flexibility corresponds to increased net injection, constrained by the rated power and the lower SoC bound as defined in (29) and (30).

Equations (31)-(37) describe the flexibility that can be provided by the EV. Downward flexibility is realized by increasing the charging power, limited by the rated charging power and the remaining capacity up to the upper SoC bound, as defined in (31) and (32). Upward flexibility is provided by reducing the charging power, limited by the maximum allowable reduction (33) and the requirement to reach the desired SoC at departure (34). It can only be offered when the available charging time (35) exceeds the required time to reach the desired SoC (36); otherwise, it is set to zero, as defined in (37). Furthermore, the HP provides downward and upward flexibility in coordination with the TSS, as expressed in constraints (38)-(41). Downward flexibility of the HP corresponds to increased electrical consumption, limited by the rated power (38), while upward flexibility corresponds to reduced electrical consumption, which cannot exceed the scheduled consumption (39). The resulting thermal output, proportional to the total electrical input via the CoP, is given by (40) and (41). The TSS compensates for these variations in the HP's thermal output to ensure that the total thermal demand is met, as enforced by the thermal balance constraints (42) and (43). The TSS operation is further constrained by its rated power and allowable SoC bounds, as defined by (44)-(47) for downward adjustments and (48)-(51) for upward adjustments.

III. Case Study and Numerical Results

The proposed MILP optimization problem is implemented in Pyomo and solved using the GLPK solver. The technical parameters and operational data of the considered DERs are obtained from the open-source OpenTUMFlex dataset, with the corresponding parameters detailed in [15]. Market data correspond to a 5-minute resolution energy market, along with two regulation Frequency Control Ancillary Services (rFCAS) markets (raise and lower) which are used to represent the market clearing prices. To align with the 15-minute time resolution of the model, the 5-minute market data are aggregated by averaging over three consecutive intervals, with the corresponding price data available in [15]. The scheduling horizon spans a full day (96 time intervals), and the prediction horizon covers the following 24 hours. For simplicity, the enabled flexibility factor is assumed to be unity.

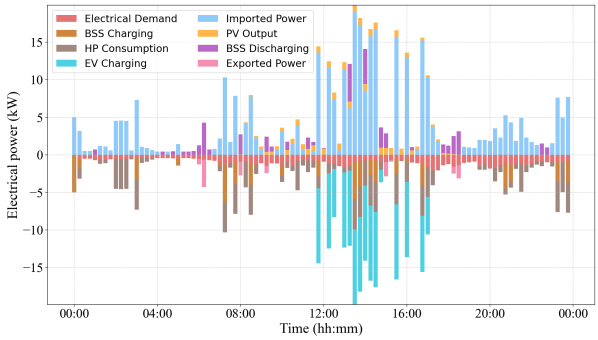

Fig. 1. Electrical power flows during a whole day

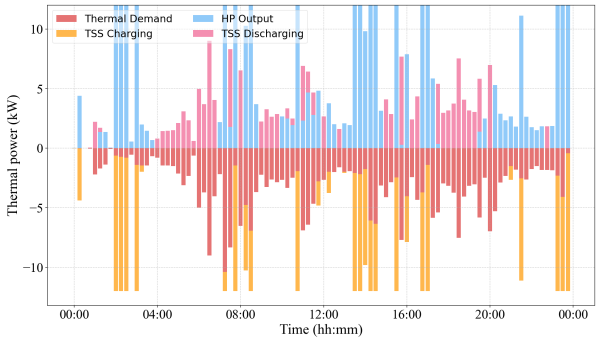

Fig. 2. Thermal power flows during a whole day

The optimization problem is solved separately for each market time interval, and the optimal scheduling of all DERs as well as their upward and downward flexibility are determined. Figs. 1 and 2 show the prosumer's electrical and thermal power flows, while Fig. 3 illustrates its flexibility provision over the whole day. These figures demonstrate that flexible DERs are optimally scheduled to perform energy and flexibility arbitrage, leveraging temporal price variations to maximize economic benefits while maintaining a balance between supply and demand. As shown in Fig. 1, the prosumer acts as an energy buyer in the majority of market intervals (over 70%), while in the remaining periods, high energy prices lead it to remain idle or strategically sell energy. In these high-price intervals, BSS discharging is clearly observed, prioritizing self-consumption over grid procurement. Similarly, EV charging is optimally distributed across plugged-in periods with lower energy prices, minimizing charging costs while ensuring the desired SoC at departure.

Moreover, the HP unit, as the only multi-energy DER in this study, is scheduled to reduce the prosumer's operational cost while efficiently interacting with the TSS to continuously meet thermal demand, as shown in Fig. 2. It is worth noting that, in the proposed model, scheduling is not solely driven by energy prices; instead, revenues from flexibility markets are also considered. As a result, the scheduling of all DERs achieves a balance between energy trading and flexibility provision to maximize the overall economic benefit. Accordingly, during market intervals where the ratio of flexibility to energy market prices is relatively high, the scheduling strategy adapts to prioritize the provision of flexibility services, thereby

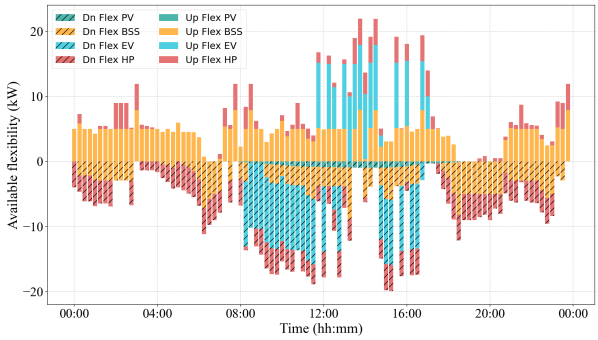

Fig. 3. Upward and downward flexibility during a whole day

TABLE I
ECONOMIC RESULTS OF PROPOSED AND SEQUENTIAL MODELS

Cost/Revenue Item	Proposed Model	Sequential Model
Energy purchase cost ($)	17.69	18.44
Energy sales revenue ($)	1.00	2.13
Up-flexibility revenue ($)	7.18	4.80
Down-flexibility revenue ($)	2.59	2.38
Total operational cost ($)	**6.91**	**9.14**

increasing the associated revenues. This behavior highlights the advantage of the proposed co-optimization framework over the sequential approach, where revenues from LFMs are not explicitly incorporated into the scheduling decisions.

To further demonstrate the effectiveness of the proposed framework, Table I summarizes its results compared to the sequential participation approach in energy and flexibility markets. This table shows that although the sequential approach achieves a slightly lower net cost from energy trading, it fails to fully exploit the revenue potential of flexibility markets. In contrast, the proposed framework enables higher revenues from both flexibility services, achieving a 36% increase compared to the sequential approach, which compensates for the marginally higher energy procurement cost. As a result, the total operational cost is significantly reduced, achieving approximately 25% cost savings compared to the sequential approach. This demonstrates the superiority of jointly considering energy and flexibility markets, as neglecting flexibility signals during scheduling leads to a loss of potential revenue.

IV. CONCLUSIONS

This paper presented a coordinated scheduling model for prosumers with multiple types of DERs participating in joint local energy and flexibility markets. An MPC-based optimization determines real-time DER scheduling as well as upward and downward flexibility provision to minimize operational cost under joint energy–flexibility constraints. Simulation results demonstrate that coordinated scheduling enables the prosumer to effectively exploit flexibility market opportunities, achieving a 36% increase in flexibility-related revenues compared to a sequential scheduling strategy. This leads to an overall reduction of approximately 25% in total operational cost. These findings highlight the importance of joint participation in energy and flexibility markets to fully exploit DER capabilities, enhancing economic benefits while supporting grid operation during critical periods.

Our proposed model relied on two simplifying assumptions that should be addressed in future research. First, the impact of activated flexibility on the resulting cost/revenue and temporal constraints was not explicitly modeled and can be incorporated in future work. Second, all relevant parameters, including market prices, generation and demand, and flexibility enabled/activated, were assumed to be perfectly forecasted. Future studies may integrate data-driven forecasting approaches to account for these uncertain parameters.

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