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Coordinated flexibility scheduling in multi-carrier integrated energy systems: a model coupling approach

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***Abstract*—Coordinating the interactions between increasingly interconnected energy sectors and carriers can lead to an efficient integration of variable renewable energy (VRE) resources, and a more cost-efficient energy transition. This paper proposes a model coupling approach that uses a market-based mechanism to efficiently coordinate the interactions among electricity, heat, and (hydrogen) gas systems, and (near) optimally schedule flexibility to maximize social welfare. The proposed approach is benchmarked against traditional co-optimization, and is shown to achieve comparable results with a moderate "optimality gap" in terms of reduction in system costs, peak load, and VRE curtailment. Its added value is the ability to enable each system to interact in an integrated energy system and locally optimize their decisions without sharing confidential information. The practical implication of this new approach is to provide a modeling environment where system operators and flexibility aggregators can obtain insights into the impacts of decarbonization of other parties on their systems—thereby avoiding myopic operational or investment decisions.**

***Index Terms*—Integrated multi-carrier energy systems, Coordinated flexibility scheduling, Model coupling**

I. Introduction

Increasing the penetration of variable renewable energy (VRE) generation in the power system and electrifying end-use sectors such as heating are key actions to decarbonize our energy system. However, high penetrations of VRE and the electrification of "everything" increase the need for flexibility in the power system. This is mainly because: (i) high penetrations of VRE increase system requirements for balancing demand and supply due to their intermittent nature; (ii) large-scale electrification of demand results in high peak flows in electricity networks, potentially causing congestion as these networks were not initially designed to accommodate such peak flows, and upgrading them is extremely slow and costly.

Interestingly, the current trend of end-use electrification enabled by Power-to-X (P2X) technologies (e.g., electrolyzers), couples different energy sectors and carriers, resulting in a multi-carrier integrated energy system (MIES). These P2X technologies are extremely flexible in operation, making these new loads inherently flexible. Coincidentally, while VRE integration and electrification increase the need for flexibility in the power system, an MIES offers a potential source of flexibility, due to its ability to shift demand or supply across different energy carriers and networks, thereby exploiting energy storage in the form of electricity, heat, or gas.

As these subsystems (electricity, heat, and gas) become increasingly interconnected, and their operations more dynamically intertwined, it becomes essential to evaluate them on a holistic level rather than as individual subsystems. Coordinating their operation can lead to an efficient integration of VRE resources, and a more cost-efficient energy transition (e.g., by reducing investment requirements in network upgrades). There is extensive literature [1], [2], showing the potential benefits of moving beyond the traditional paradigm of independently operating these subsystems, to coordinating and operating them as one whole MIES, that is, a system of systems.

However, energy system integration and the inclusion of many different types of flexibility resources increase the complexity of the energy system—it brings significant challenges to coordinating their operations [3]. Uncoordinated operations could accentuate VRE integration challenges. For example, local flexibility resources can aggravate congestion in the electricity distribution network if they simultaneously ramp up power consumption in response to low electricity prices. Therefore, energy system integration brings along a methodological challenge—the challenge of coordinating the interactions among subsystems with multiple flexibility resources and optimally schedule flexibility to maximize social welfare.

The remainder of this paper is structured as follows. Literature on the state-of-the-art approaches to flexibility scheduling in MIESs is reviewed in section II. The case study and the proposed approach to flexibility scheduling based on model coupling are introduced in section III. Next, results and discussion are presented in section IV. Finally, the conclusion and future research directions are summarized in section V.

II. Literature review

The traditional approach to model coordinated flexibility scheduling in MIESs is based on co-optimization. Co-optimization is a monolithic approach in which the operation (control) of all subsystems and flexible consumer assets is optimized using a standalone computational tool. Although widely adopted in the literature [4], [5], this overarching approach has several limitations: (i) it assumes that a central entity has perfect information and full control over all subsystems, and dispatches them to minimize system costs. This assumption implies that subsystem operators (e.g., a heat grid operator) give up control over their assets, raising an autonomy issue due to its top-down control mechanism; (ii) it is limited in the way it represents consumer behavior due to the simplifying assumption on coordination strategies (top-down control); (iii) it requires complete information regarding the flexibility of consumers and the internal states of their assets. This raises a privacy issue as in reality, flexible consumers might not be willing to share such information due to confidentiality reasons; (iv) it does not scale well as it becomes computationally challenging to solve if all subsystems are modeled in high spatiotemporal and techno-economic detail [6].

Generally, distributed optimization techniques can be applied to address the issue of privacy and autonomy, as they enable flexible consumers to optimize their decisions locally without sharing confidential information or giving up control. Such techniques usually rely on iteratively adjusting electricity prices in a way that reflects system-wide demand and supply imbalance [7]. However, it often requires many iterations before converging [8], which can significantly slow down the simulation time for large complex systems such as MIESs. In some cases, depending on the initialization or price update algorithm, it might even fail to converge for non-convex optimization problems [3]. Thus, the need arises to develop a scalable approach that can include confidential information about flexibility in system-wide energy models.

To address these limitations, this paper proposes a new approach to model coordinated flexibility scheduling in MIESs—a model coupling approach based on willingness-to-pay (WTP) information exchange. In this non-iterative approach, a model coupling framework is developed to coordinate the interactions among subsystems through a market-based mechanism. Each flexible consumer (satellite) model interacts with an electricity market (central) model by only sharing their WTP, expressed as a sequence of price-quantity bid pairs. In return, the central model determines the electricity prices and the demand satisfied for each satellite model.

This approach overcomes the limitations of distributed and co-optimization. First, flexible consumers do not have to give up control over their assets. Second, they do not have to share any confidential information. How they determine their WTP is their confidential trade strategy encapsulated in their respective models. Third, it allows for a better representation of consumer behavior and their bidding strategies, avoiding simplifying assumptions on coordination strategies. Finally, this approach scales well with the level of detail in the models, making it possible to model complex systems with the desired level of accuracy. This is because each subsystem can be simulated in parallel in its native tool with a separate dedicated solver, significantly increasing computational power. We compare the performance of this new approach with traditional co-optimization using metrics such as system costs, peak load, and VRE curtailment, and show that it achieves comparable results with a moderate "optimality gap". In sum, the main contribution of this paper is to propose a new approach to efficiently coordinate the interactions among electricity, heat, and gas systems with distributed flexibility resources in an MIES, and "near" optimally schedule flexibility to maximize system-wide social welfare.

III. Methodology

This section first introduces the methodological case study of the MIES considered, and then describes the models and mathematical formulations under uncoordinated and coordinated (co-optimization and model coupling) scheduling. The implementations have been archived on Zenodo [9], [10].

A schematic illustration of the MIES is shown in Fig. 1. It consists of a heat, transport, and (hydrogen) gas system coupled to the electricity system through P2X technologies. The heat, transport, and gas systems have storage to buffer consumption, making their demand flexible in time.

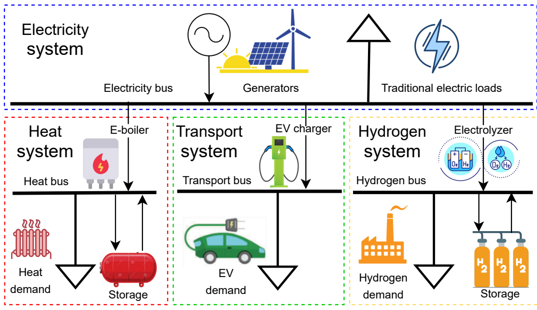


Fig. 1. Schematic representation of the MIES.

The electricity system consists of VRE and some conventional generators (not shown) that provide backup during periods of low VRE generation and peak demand. Data is taken from the German Sci-Grid model[0]. The data used include generator types, their marginal costs, installed capacities, hourly capacity factor timeseries for VRE generators, and three demand types with hourly load profiles. We assumed that each demand has some flexibility such that it can shift electricity consumption to earlier or later timesteps by a few hours.

A. *Uncoordinated flexibility scheduling*

In the uncoordinated approach, each system (heat, transport, and gas), given (pre-response) electricity price signals λ_t, schedules its flexibility (electricity consumption) independently by solving the full cost minimization problem described by *Problem 1* over the scheduling horizon H.

$$\textit{Problem 1:} \qquad \min_{p_t^G, h_t, e_t} \sum_t^H \lambda_t \cdot p_t^G \tag{1}$$

$$\text{s.t.} \qquad p_t^G = L_t + h_t, \quad \forall \quad t \tag{2}$$

$$P_{p2x}^{min} \leq p_t^G \leq P_{p2x}^{max}, \quad \forall \quad t \tag{3}$$

$$e_t = e_{t-1} + h_t, \quad \forall \quad t \tag{4}$$

$$E_t^{min} \leq e_t \leq E_t^{max}, \quad \forall \quad t \tag{5}$$

$$e_T = E^{CAP} \tag{6}$$

[0]https://pypsa.readthedocs.io/en/latest/examples/scigrid-lopf-then-pf.html

where p_t^G is the electricity from the day-ahead market and P_{p2x} is the capacity of the P2X technology. L_t and h_t are the inflexible and flexible demands, respectively. h_t is modeled as a store with constraints on the energy level e_t and a deadline at which the store must be charged to full capacity E^{CAP} (demand must be fully satisfied at the final timestep T in H).

After solving *Problem 1*, the resulting electricity consumption of each system is aggregated into a load profile seen by the electricity system. The electricity system then performs an economic dispatch optimization described by *Problem 2* to satisfy the total load D_t of the MIES.

$$\textit{Problem 2:} \qquad \min_{p_{g,t}} \sum_{g,t}^{H} C_g \cdot p_{g,t} \tag{7}$$

$$\textit{s.t.} \qquad \sum_{g} p_{g,t} = D_t, \quad \forall \quad t \tag{8}$$

$$\tilde{A}_{g,t} \cdot P_g^{nom} \leq p_{g,t} \leq \hat{A}_{g,t} \cdot P_g^{nom}, \quad \forall \quad g, t, \tag{9}$$

where C_g is the marginal cost of generators, $p_{g,t}$ is the dispatch constrained by their nominal capacities P_g^{nom} and per unit time-dependent availabilities $\tilde{A}_{g,t}$ and $\hat{A}_{g,t}$.

B. Coordinated scheduling using centralized co-optimization

This approach assumes that a central entity has perfect information and full control over all assets in the MIES, and schedules flexibility through a top-down control mechanism by solving the cost minimization problem described in *Problem 3*, which is implemented in the open source tool PyPSA [11].

$$\textit{Problem 3:} \qquad \min_{p_{g,t}, h_{p2x,t}, e_{p2x,t}} \sum_{g,t}^{H} C_g \cdot p_{g,t} \tag{10}$$

$$\textit{s.t.} \quad (9) \quad \text{and} \sum_{g} p_{g,t} = \sum_{p2x} L_{p2x,t} + \sum_{p2x} h_t, \forall p2x, t \tag{11}$$

$$e_{p2x,t} = e_{p2x,t-1} + h_{p2x,t}, \quad \forall \quad p2x, t \tag{12}$$

$$E_{p2x,t}^{min} \leq e_{p2x,t} \leq E_{p2x,t}^{max}, \quad \forall \quad p2x, t \tag{13}$$

$$e_{p2x,T} = E_{p2x}^{CAP} \quad \forall \quad p2x \tag{14}$$

C. Coordinated scheduling using model coupling

Here, we propose a non-iterative model coupling approach using WTP information exchange (a market-based control mechanism) to coordinate flexibility scheduling. A schematic illustration of the model interactions is shown in Fig. 2.

Satellite models interact with the central model by only sharing their WTP, which conveys information about how much electricity they are willing to consume at a given price. This lets satellite models keep their operational details and bidding strategy confidential, as they are encapsulated in their respective models (a "black box" to other interacting models).

For this work, satellite models are implemented as a cost minimization heuristic strategy with the same parameters as in *Problem 1*. Demand is kept in a queue: inflexible demand at the front of the queue is bid for at the market ceiling price, and flexible demand further in the queue that could still be satisfied in future timesteps, is bid for at a price linearly decreasing from the ceiling to floor price.

The central model represents a day-ahead electricity market model that maximizes social welfare based on the WTP from satellite models and generator marginal cost and capacities. The formulation is shown in *Problem 4*, where $\mu_{p2x,t}$ and $d_{p2x,t}$ are the price-quantity bid pairs (WTP) of satellite models.

$$\textit{Problem 4:} \quad \max_{p_{g,t}, d_{p2x,t}} \sum_{p2x} \mu_{p2x,t} \cdot d_{p2x,t} - \sum_{g} C_g \cdot p_{g,t} \tag{15}$$

$$\textit{s.t.} \quad (9) \quad \text{and} \quad \sum_{g} p_{g,t} = \sum_{p2x} d_{p2x,t}, \quad \forall \quad t \tag{16}$$

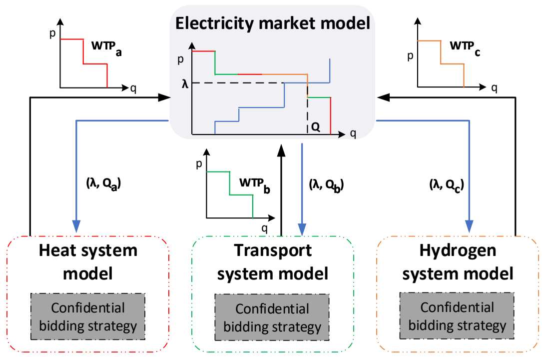


Fig. 2. Model interactions using WTP information exchange.

These models are coupled together using the third incarnation of the MUltiScale Coupling Library and Environment (MUSCLE3) [12]. As shown in Fig. 3, MUSCLE3 provides a manager component that starts all submodels whose implementations are wrapped in a so-called libmuscle instance. The manager sets up direct peer-to-peer network connections, and manages message (data) exchange between submodels. The configuration is specified in a yMMSL (YAML Multiscale Modeling and Simulation Language) file. Once instantiated, each independently running submodel can interact with the other models by sending and receiving messages over the connecting ports set up by the manager component. At every time t, satellites initialize the simulation by updating their internal states. Next, they construct and send their WTP to the central model. Central then clears the market and reports the price and demand satisfied. The simulation proceeds to the next timestep $t+1$ until the final step T. A schematic illustration of this procedure is shown in Fig. 4.

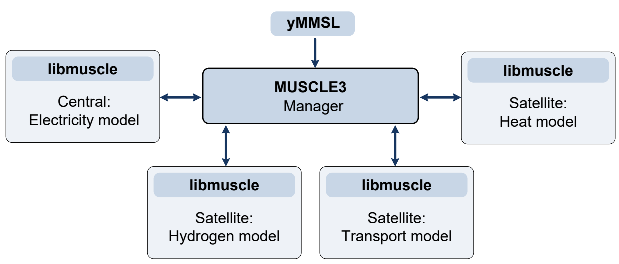


Fig. 3. MUSCLE3 architecture (high-level) components.

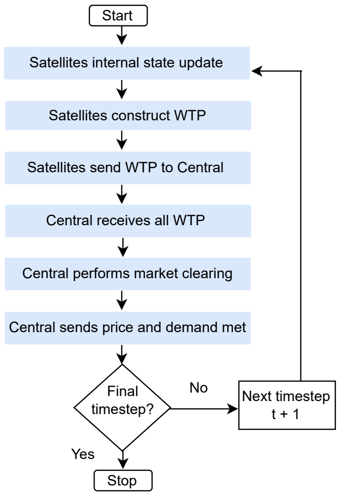


Fig. 4. Simulation execution flowchart

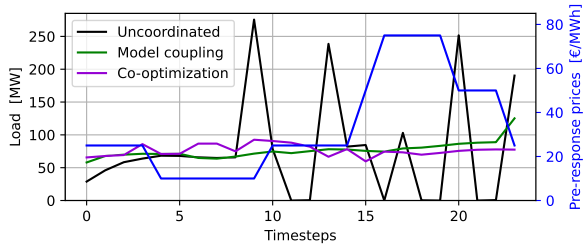
IV. Results and Discussion

An hourly operation (the time resolution for both the central and satellite models in this study is 1 hour) of the MIES was investigated over a daily scheduling horizon. The difference between the uncoordinated and coordinated scheduling approaches is quantified using system realized load, VRE curtailment, electricity prices, and operational costs—defined as the sum of all dispatched power times the marginal cost of dispatched generators.

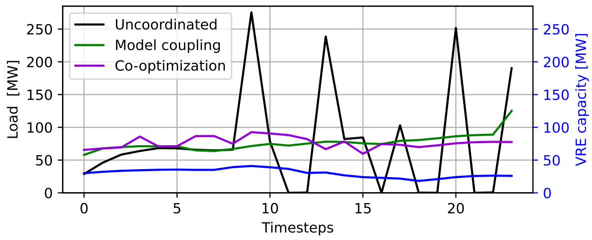
As shown in Fig. 5, uncoordinated flexibility scheduling results in multiple peaks in the realized load profile since each subsystem tries to schedule consumption during low (pre-response) price time periods (due to high VRE availability). The lack of coordination results in over-consumption during high VRE generation periods, shifting consumption completely away from some periods of moderate VRE generation, leading to VRE curtailment. Moreover, the final electricity prices obtained no longer represent the (pre-response) prices against which these subsystems optimized their operations. This highlights the limitations of current practices that neglect coordination and model flexibility scheduling (demand response) with no feedback on the wholesale market.

Conversely, the realized load profile from model coupling and centralized co-optimization approaches have substantially lower peaks and no VRE curtailment, that is, both approaches result in an efficient integration of VRE generation. This demonstrates the practical implications of the proposed approach—it can achieve an efficient coordination between price-responsive demand and VRE generation. The load profiles under both coordinated scheduling approaches also have a similar trajectory, except that a higher peak occurs in the final timestep of the model coupling approach.

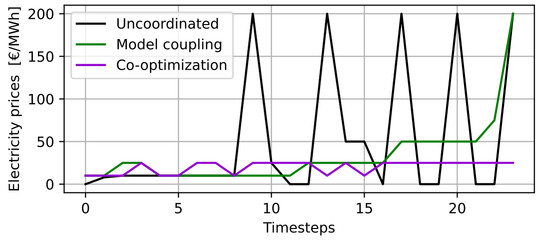
The peak at the final timestep can be attributed to two main reasons. The first is because of the simple bidding strategy adopted for all satellite models, which keeps bidding low for flexible demand that can still be satisfied in later timesteps.



(a) Realized load



(b) VRE curtailment (area between load and VRE capacity)

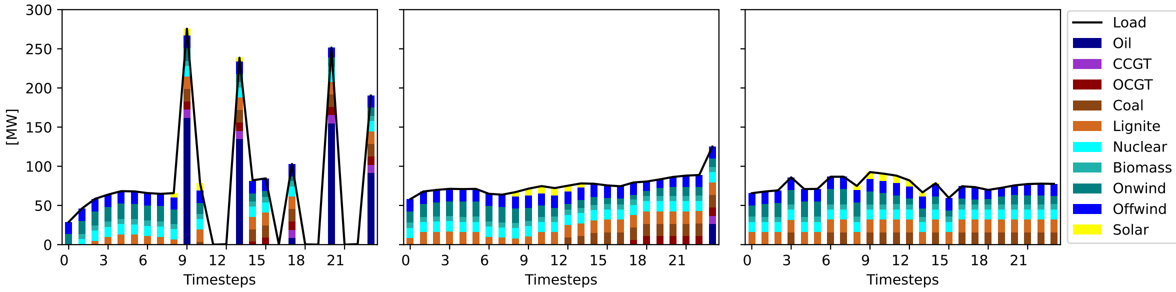


(c) Electricity prices

Fig. 5. Realized load, VRE curtailment, and electricity prices.

However, as the deadline approaches, all satellite models start increasing their bid prices for any unsatisfied demand as shown in the last illustration of Fig. 5. This behavior can be avoided by adopting different bidding strategies for each satellite model, using different price curves with different slopes (rather than a simple linear interpolation from the ceiling to floor prices), or using intelligent adaptive approaches such as reinforcement learning. Applying these to approximate an "ideal" optimum is a relevant extension for future work. The second reason can be attributed to the impact of decision-making in hindsight (imperfect information). Achieving the "ideal" optimum of centralized co-optimization which assumes perfect foresight is very difficult in practice, since one cannot guarantee the same optimality if a subsystem operator or flexible consumer would have made different choices in hindsight.

The dispatch of generators is shown in Fig. 6. The uncoordinated approach results in expensive units (e.g., Oil) being dispatched more often, while VRE generation is curtailed, resulting in an inefficient operation of the MIES. Under both coordinated approaches, expensive generators are only dispatched when the available VRE generation capacity is fully utilized. While Oil and CCGT units are dispatched in the final timestep under model coupling, the perfect foresight of co-optimization avoids this by increasing the dispatch of



(a) Uncoordinated (b) Model coupling (c) Co-optimization

Fig. 6. Generator dispatch.

moderately expensive units in earlier timesteps that would otherwise result in expensive units being dispatched later.

Finally, Table I shows the reduction in system operational costs, peak load (an important metric used by network operators to plan network reinforcement), and VRE curtailment relative to the uncoordinated approach (reference case). The difference in the reduction in system operational costs, peak load, and VRE curtailment between the model coupling approach and co-optimization is about 6%, 12%, and 0%, respectively. This can be interpreted as the "optimality gap" between these two approaches, with co-optimization being the lower bound, which is not achievable in practice due to imperfect foresight and limited information in real world.

V. Conclusion

This paper proposes a model coupling approach that uses a market-based mechanism to coordinate the interactions among electricity, heat, and gas systems to "near" optimally schedule flexibility. The proposed approach is non-iterative and does not require interacting systems to give up control over their systems. It is benchmarked against traditional centralized co-optimization, and shown to achieve comparable results with a moderate "optimality gap". Its added value is the ability to allow each system to interact in an MIES and locally optimize its decision without sharing confidential details, thereby providing a modeling environment where system operators or flexibility aggregators can obtain insights into the impacts of decarbonization of other parties on their systems. Another expected advantage is scalability, since the systems can be independently simulated in parallel, each using a dedicated solver. A relevant extension for future work will be a scalability test to investigate how this approach scales with the number of coupled models, their level of detail (e.g., unit commitment), and the length of the scheduling horizon, in comparison with centralized optimization and distributed optimization (equilibrium modeling) of a large scale MIES.

TABLE I
Reduction in system costs, peak load, and VRE curtailment

Scheduling approach	**Uncoordinated** (reference)	**Model coupling**	**Co-optimization**
System costs	-	83%	89%
Peak load	-	54%	66%
Curtailment	-	100%	100%

VI. Acknowledgments

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