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Model Predictive Control for Optimized Energy Exchange Between Model Predictive Control for Optimized Energy Transfer Between Two Renewable Energy Producers and Consumers

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ABSTRACT

This study investigates optimizing energy exchanges between two prosumers—entities that both produce and consume energy—equipped with renewable energy sources, loads, and storage. Leveraging a Model Predictive Control (MPC) framework, the system balances energy production and consumption, reducing dependency on the grid while promoting higher renewable energy utilization. The MPC method integrates future forecasts of renewable supply and demand, enabling real-time, proactive management of energy flows and promoting efficient usage of available resources. At each control interval, the MPC evaluates data and forecasts to optimize energy dispatch between renewable sources, batteries, and loads, as well as manage surplus energy exchanges between prosumers, reducing waste and increasing efficiency. This coordination led to an increase in renewable penetration from 71% to 84% in simulations, demonstrating the advantages of prosumer cooperation in meeting variable energy demands.

The framework’s flexibility also enables response to renewable variability, such as solar intermittency, and can be expanded to include larger prosumer networks or additional storage, enhancing grid resilience. Ultimately, this research underscores MPC's potential in fostering efficient, sustainable, and flexible distributed energy systems by optimizing energy exchanges, increasing renewable penetration, and reducing grid dependency.

flexibly to the variability of renewable energy sources. This can be particularly beneficial in scenarios where renewable generation is intermittent, such as with solar panels during cloudy periods or wind turbines during calm weather. Moreover, the MPC-based control system could easily be expanded to accommodate a larger network of prosumers or additional energy storage solutions, further enhancing the grid’s resilience and renewable energy utilization.

In summary, this research highlights the potential of MPC-based control systems for optimizing energy exchanges between prosumers, improving renewable energy penetration, and reducing dependence on conventional grid power. By coordinating renewable energy flows and energy storage usage, this approach paves the way for more efficient, sustainable, and flexible distributed energy systems in the future.

Keywords :.Renewable Energy, model predictive control (MPC), The two prosumers.

1. INTRODUCTION

Figure 1 illustrates a block-diagram representation of the Model Predictive Control (MPC) system, showcasing its operational framework. In this setup, the core component is a process model that predicts future system outputs by analyzing historical inputs and outputs. Based on these predictions, the MPC generates optimized control signals for the system's future operation. The optimization process within the MPC takes into account various constraints, such as system limitations and operational boundaries, and works toward an objective function that defines the desired performance outcomes, like minimizing energy costs or maximizing renewable energy utilization.

One of the key elements of the MPC is its ability to track a reference trajectory, which represents the ideal behavior or performance target for the system. The MPC continuously evaluates the difference between the predicted outputs from the process model and this reference trajectory, adjusting the control signals to bring the system closer to the target. This closed-loop approach allows the MPC to make dynamic, real-time decisions that adapt to changing conditions, such as fluctuations in renewable energy supply or shifts in energy demand.

The effectiveness and precision of the MPC algorithm are directly influenced by the accuracy of the process model it relies upon. If the model can accurately forecast future conditions—such as solar irradiance or wind speeds in a renewable energy system—the control decisions will be more effective in optimizing the system's performance. Conversely, inaccuracies in the model can lead to suboptimal control actions, which may reduce the efficiency of energy dispatch or lead to greater reliance on grid power. Therefore, the development and fine-tuning of the process model play a critical role in the success of the MPC strategy.

By integrating these predictive capabilities with real-time control, the MPC framework offers a robust approach to managing complex energy systems, especially in environments with variable renewable energy sources. It ensures that energy flows are optimized while respecting system constraints, leading to enhanced performance, lower operational costs, and higher renewable energy utilization. [1].

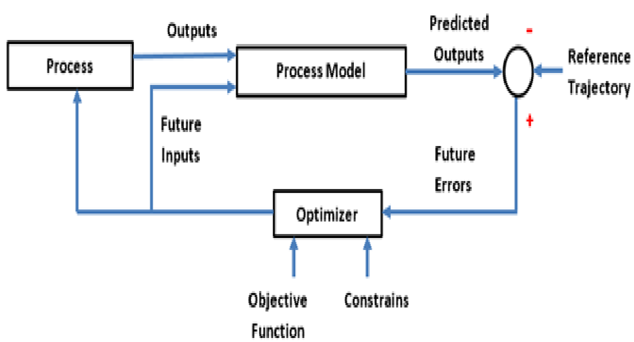

Figure 1: General MPC control flow

2. PROBLEM FORMULATION

Figure 2 provides a detailed depiction of the primary components of the two interconnected prosumers analyzed in this study, alongside the power flow pathways between them. These prosumers are each equipped with renewable energy generation, battery storage systems, and their respective loads. The Model Predictive Control (MPC) algorithm is engineered to optimize energy dispatch between the two prosumers, aiming to maximize the consumption of locally generated renewable power while minimizing reliance on external energy sources, such as the broader electrical grid or other retail energy providers. By minimizing energy exchanges with external networks, the MPC strives to achieve greater energy independence for the two prosumers. Essentially, it works to isolate their operations, ensuring that most, if not all, of their energy demands are met through locally generated renewable energy and stored battery power. This strategic isolation helps reduce energy trading costs, grid dependency, and ensures more efficient use of renewable resources, even under variable production conditions.

The remainder of the study breaks down the components of the MPC problem, beginning with a detailed battery storage model that describes how energy is stored and retrieved in each prosumer's battery system. The state-space formulation follows, defining the mathematical framework through which the system's dynamics are modeled and controlled. This provides a systematic way of representing both the energy flows and the decision-making process within the MPC.

Next, the objective function is established, which serves as the guiding principle for the MPC. The function is designed to prioritize the use of renewable energy, minimize external energy purchases, and optimize battery utilization. At the same time, it incorporates key performance metrics such as cost savings, energy efficiency, and renewable penetration.

The MPC algorithm also incorporates a reference trajectory, which is based on forecasted information regarding future energy demand and renewable energy production. These forecasts play a crucial role in shaping the control strategy, as they allow the MPC to make proactive, rather than reactive, decisions about energy flows. Accurate predictions enable better alignment of renewable energy generation with consumption, further reducing reliance on external energy.

Finally, all system constraints are defined, including physical limitations like battery capacity, load demands, and renewable generation variability. The MPC must operate within these boundaries, ensuring that while it seeks to optimize performance, it does so without exceeding the system's inherent limits. These constraints ensure realistic and feasible solutions within the modeled energy system.

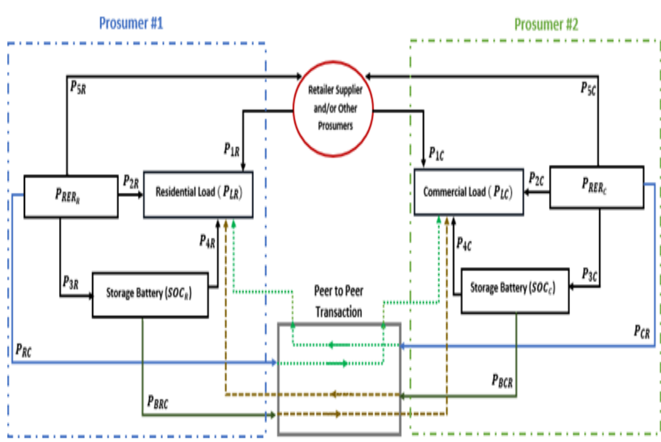

Figure 2: Coupled microgrid block diagram with two prosumers. Energy transfers between elements are simulated on an hourly basis, according to MPC algorithm that maximizes Energy penetration.

3. MPC OBJECTIVE FUNCTION and REFERENCE TRAJECTORY

The primary objective of the control system is to minimize the reliance on backup energy sources while maximizing the consumption of renewable energy directly by the load. Although the use of battery or thermal storage is necessary to balance supply and demand, it should be minimized to reduce energy losses and mitigate the impact on the longevity of the storage systems. The following equation outlines the comprehensive objective that the control system seeks to minimize, serving as a foundation for developing the state-space representation.

$$J = \sum_{K=0}^{T} \{ \; C_1^2 \; [P_{1R}(k) + P_{1C}(k)]^2 \quad C_2^2 \; [P_{3R}(k) + P_{3C}(k) + P_{4R}(k) + P_{4C}(k)]^2 + \; C_3^2 \; [P_{RC}(k) + P_{CR}(k)]^2 + \; C_4^2 \; [P_{RC}(k) + P_{CR}(k)]^2 + \; C_5^2 \; [P_{RER\,R}(k) - P_{2R}(k) + P_{3R}(k) - P_{RC}(k)]^2 + \; C_5^2 \; [P_{RER\,C}(k) - P_{2C}(k) + P_{3C}(k) - P_{CR}(k)]^2 \} \; \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \; (1)$$

At each time step, the Model Predictive Control (MPC) objective function is calculated by summing all 10 components listed in Table 1. This function anticipates future energy demands over a defined time horizon, denoted by NP, and aggregates energy-related terms across a specified time interval at T.

Table 1: System outputs and objective terms

System outputs	Objective function terms	Description (R – residential prosumer) (C – commercial prosumer)
$y_{mR} = C_1[P_{2R} + P_{4R} + P_{CR} + P_{BCR}]$	$J_{1R} = C_1^2 P_{1R}^2 = [C_1 P_{LR} - y_{mR}]^2$	Energy purchased from other network prosumers or retail suppliers
$y_{mC} = C_1[P_{2C} + P_{4C} + P_{RC} + P_{BRC}]$	$J_{1C} = C_1^2 P_{1C}^2 = [C_1 P_{LC} - y_{mC}]^2$	
$y_{aR} = C_2(P_{3R} + P_{4R})$	$J_{2R} = C_2^2(P_{3R} + P_{4R})^2 = y_{aR}^2$	Charging and discharging energy transfer to battery
$y_{aC} = C_2(P_{3C} + P_{4C})$	$J_{2C} = C_2^2(P_{3C} + P_{4C})^2 = y_{aC}^2$	
$y_{bR} = C_3 P_{5R}$	$J_{3R} = C_3^2 P_{5R}^2 = y_{bR}^2$	Energy sold to other network prosumers
$y_{bC} = C_3 P_{5C}$	$J_{3C} = C_3^2 P_{5C}^2 = y_{bC}^2$	
$y_{dR} = C_4 P_{RC}$	$J_{4R} = C_{4R}^2 P_{RC}^2 = y_{dR}^2$	Energy transferred from the residential RER supply to the commercial load, and vice versa
$y_{dC} = C_4 P_{CR}$	$J_{4C} = C_4^2 P_{CR}^2 = y_{dC}^2$	
$y_{eR} = C_5 P_{BRC}$	$J_{5R} = C_{5R}^2 P_{BRC}^2 = y_{eR}^2$	Energy transferred from the residential battery to the commercial load, and vice versa
$y_{eC} = C_5 P_{BCR}$	$J_{5C} = C_5^2 P_{BCR}^2 = y_{eC}^2$	

The following equation and definitions are used to recursively update these energy levels.

$$X_m(k) = X_m(k-1) + b_m \, u(k-1) \ldots\ldots\ldots\ldots\ldots\ldots \; (2)$$

$$\boldsymbol{u(k) = [P_{2R}, \ P_{2C}, \ P_{3R}, P_{3C}, \ P_{4R}, P_{4C}, P_{RC}, P_{CR}, P_{BRC}, P_{BCR}]^T} \ldots\ldots\ldots\ldots\ldots\text{....(3)}$$

$$b_m = \begin{bmatrix} 0 & 0 & \eta c & 0 & -\eta D & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \eta c & 0 & -\eta D & 0 & 0 & 0 & 0 \end{bmatrix}$$

state-space model and Reference Trajectory

$$x(k+1) = Ax(k) + Bu(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$
$$y(k) = Cx(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

$$A = \begin{bmatrix} I_{2\times10} & 0_{2\times10} \\ 0_{10\times2} & 0_{10\times10} \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 & \eta_c & 0 & -\eta_D & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \eta_C & 0 & -\eta_D & 0 & 0 & 0 & 0 \\ C_1 & 0 & 0 & 0 & C_1 & 0 & 0 & C_1 & 0 & 0 \\ 0 & C_1 & 0 & 0 & 0 & C_1 & C_1 & 0 & 0 & 0 \\ C_3 & 0 & C_3 & 0 & 0 & 0 & C_3 & 0 & 0 & 0 \\ 0 & C_3 & 0 & C_3 & 0 & 0 & 0 & C_3 & 0 & 0 \\ 0 & 0 & C_2 & 0 & C_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & C_2 & 0 & C_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & C_4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & C_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & C_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & C_5 \end{bmatrix},$$

$$R = [C_1 P_{LR}(k), C_1 P_{Lc}(k), C_5 P_{RER\ R}(k)\ C_5 P_{RER\ C}(k) \ldots\ldots C_1 P_{LR}(k+N_p|k), C_1 c(k+N_p|k), C_5 P_{RER\ R}(k+N_p|k), C_5 P_{RER\ c}(k+N_p|k)] \ldots\text{.(6)}$$

4. RESULTS

Figure 3 The figure below presents the monthly total energy exchanged between the paired prosumers, highlighting the flow of energy across different seasons. It illustrates a noticeable seasonal variation, where a greater amount of energy is transferred from the residential prosumer to the commercial prosumer during the summer months, compared to the winter. This seasonal disparity can be attributed to higher energy demand in the commercial sector during the warmer months, potentially due to increased cooling requirements, while residential loads may experience a reduction during this period. Conversely, during the winter, energy transfers are more balanced or may even shift, as residential heating demands increase, influencing the dynamic between the two prosumers.

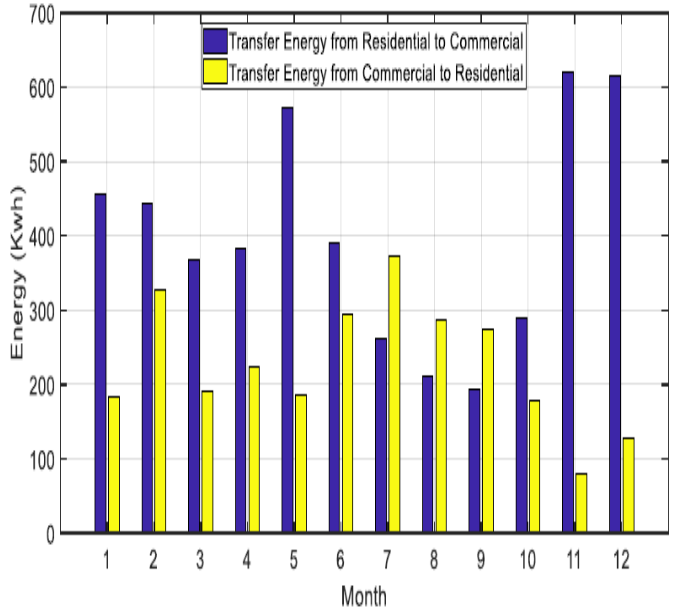

Figure 3: Monthly total energy transfers between the two prosumers.

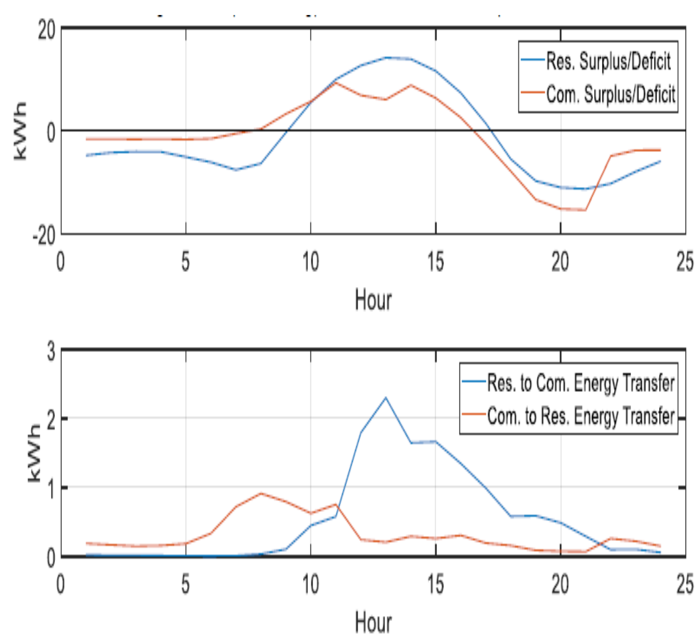

Figure 4: Average daily energy transfers between the two prosumers

After running both algorithms for an entire year, it becomes feasible to derive summary performance metrics such as renewable energy penetration and curtailment levels. The findings for these metrics are presented in Table 2, which provides a comparative analysis of the results obtained from paired versus unpaired Model Predictive Control (MPC) operations. When the two prosumers operate independently (unpaired), the overall percentage of their energy loads satisfied by renewable energy resources (RER) is recorded at 75%. In contrast, when these loads are paired together, this percentage significantly rises to 86%. This increase in renewable energy utilization underscores the advantages of coordinated energy management between the prosumers, illustrating how effective load sharing can enhance overall renewable penetration and optimize energy use.

Table 2: Performance for both operating modes

	Unpaired	Paired
Percentage of both loads satisfied by RER production	71%	84%
Percentage of total RER output transferred to other prosumers	39%	32%

Figure 5 The following graphs depict the average daily performance of both prosumers over the entire year, focusing on the surplus of renewable energy resources (RER). This surplus is calculated by subtracting the energy load from the energy production of each prosumer. The plots clearly illustrate the periods during which each prosumer experiences a surplus—indicating that their RER output exceeds their energy demands—as well as the intervals when they face a deficit, characterized by a shortfall in energy production relative to their load requirements. These visualizations provide valuable insights into the energy dynamics of the prosumers, highlighting not only their renewable energy production patterns but also the times when energy management strategies may be necessary to address the gaps in energy supply.

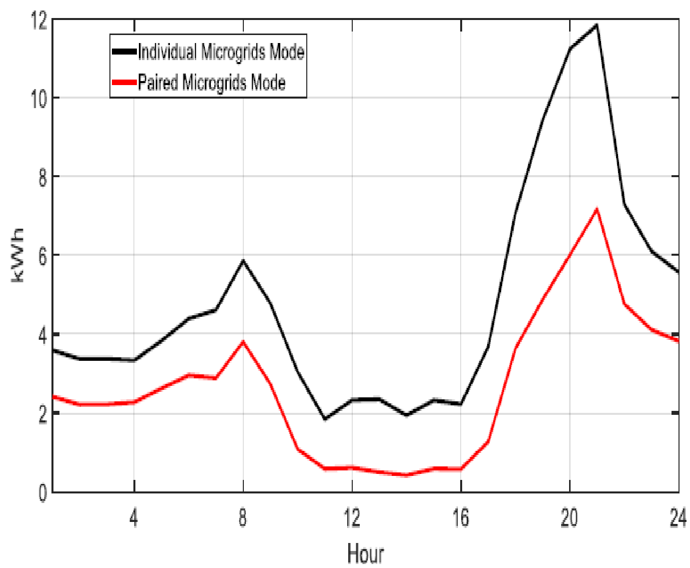

Figure 5: Average daily energy from external prosumers to both prosumers.

Figure 6 and **Figure 7** presents illustrative examples of the demand and supply profiles for both residential and commercial systems. Each subplot features a vertical line that marks the current time, denoted as k.
k, which corresponds to midnight. To the left of this line, one can observe a day's worth of historical data, showcasing the actual demand and supply trends leading up to the present

moment. Conversely, to the right of the vertical line lies a day of forecasted values, depicting projected demand and supply patterns for the immediate future.

Additionally, the graph includes actual future load and supply data, which would typically be unavailable in a real-world scenario, to highlight the discrepancies that can occur between forecasted and actual values. This comparison emphasizes the potential for forecasting errors, providing a comprehensive view of how demand and supply dynamics can fluctuate and the challenges associated with accurately predicting energy needs.
predicting energy needs.

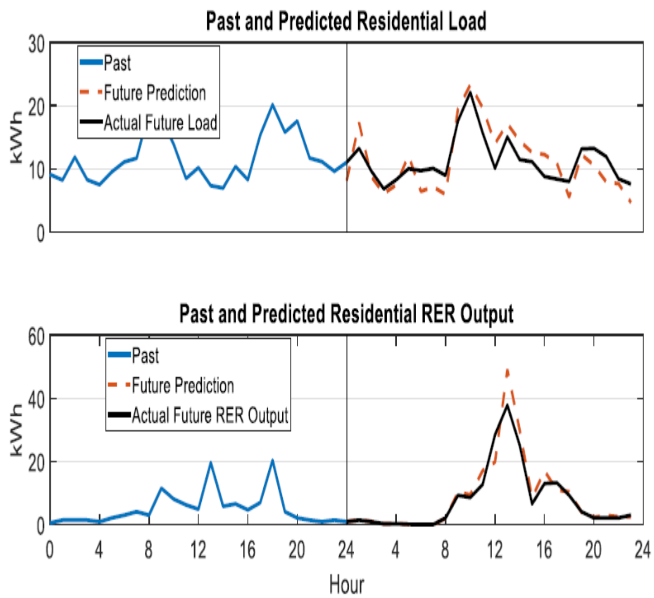

Figure 6: Two days of Residential demand and supply profiles used in simulation.

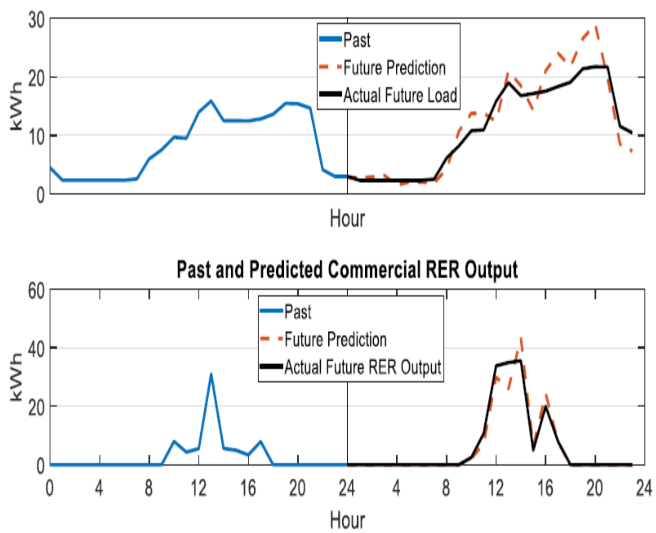

Figure7: Two days of Commercial demand and supply profiles used in simulation.

5. CONCLUSIONS

This research underscores the substantial benefits of employing a Model Predictive Control (MPC) framework to enhance the efficiency of energy exchanges between two prosumers, each possessing its own renewable energy generation capabilities and battery storage systems. Previous studies primarily focused on optimizing energy management within a single prosumer's system. In contrast, this work introduces a cohesive MPC dispatch algorithm designed to simultaneously manage all internal energy flows of the paired prosumers, as well as the shared energy transactions that occur between them.

The integration of two distinct prosumers allows for a more dynamic interaction, capitalizing on the variability in their respective supply and demand profiles. As a result, this collaborative approach leads to a notable increase in renewable energy penetration when compared to scenarios where each prosumer operates independently. The case study presented features a residential prosumer paired with a commercial prosumer, illustrating the practical advantages of this synergistic model.

The MPC framework leverages advanced predictive analytics to anticipate fluctuations in both energy supply and demand, thereby enabling proactive management of the battery storage systems. By ensuring that batteries are discharged during periods of expected surplus and charged prior to anticipated demand peaks, the algorithm optimizes energy utilization, minimizes reliance on external grid sources, and reduces overall operational costs.

Moreover, the findings indicate that renewable energy penetration could be further enhanced by expanding the MPC strategy to include additional prosumers within the energy network. However, the complexity of the current MPC formulation presents challenges in scalability, particularly as the number of variables increases with each added prosumer. One viable strategy for addressing these scalability challenges could involve limiting the MPC application to manage only the shared energy flows between prosumers, while allowing each prosumer to independently manage its internal energy dynamics.

This approach would not only simplify the optimization process but also maintain the advantages of cooperative energy management, ultimately leading to a more resilient and sustainable energy ecosystem. Future research could explore the potential for implementing this hybrid approach, as well as its implications for broader energy markets and policies aimed at promoting decentralized renewable energy generation.

In conclusion, the utilization of MPC in managing energy exchanges between prosumers presents a promising pathway for maximizing renewable energy use, enhancing system reliability, and fostering a more sustainable energy future. By continuing to refine and expand this approach, we can better support the transition toward a decentralized energy landscape that benefits both consumers and producers alike.

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