

Article

Structural Market Power in the Presence of Renewable Energy Sources

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Abstract: Assessing market power in the presence of different production technologies such as renewable energies, including wind and solar power, is crucial for electric market analysis and operation. This paper investigates structural market power by incorporating wind farms and solar generation over a short-term period. The study examines the issue of market concentration boundaries to assess structural market power by calculating the minimum and maximum market concentration index values in the day-ahead market. It models the technical specifications of power plants, such as the maximum and minimum production limits, ramp-up and ramp-down rates, and minimum required up and down times. By extracting the spatiotemporal correlation of wind power generation from real data, the uncertainty of renewable power generation is represented through a set of scenarios. The analysis explores the correlation effects of wind farms, solar generation, and wind penetration levels under different ownership structures. Simulation results using a modified PJM five-bus system illustrate the effectiveness of the developed method. Our results indicate that integrating renewable energy can reduce the Herfindahl–Hirschman Index (HHI) by up to 30% as wind penetration levels rise from 0% to 40%, fostering a more competitive market structure. However, the correlation between wind farms also increases market volatility, with the standard deviation of the HHI rising by about 25% during peak load periods. These findings demonstrate the practical applicability of the developed methodology for assessing market dynamics in the presence of renewable energy sources.

Keywords: electricity market; renewable energy sources; wind energy; solar systems; market power



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1. Introduction

The integration of renewable energy sources (RESs), particularly wind and solar power, is rapidly transforming electricity markets globally. This transformation introduces significant challenges and opportunities related to market power—the ability of firms to influence market prices. Understanding market power is critical in the electricity market due to high investment costs, inelastic short-term demand, the need for real-time balancing of supply and demand, and significant energy storage costs [1]. RESs like wind and solar power bring substantial variability and uncertainty into electricity markets. This uncertainty is further exacerbated by the spatiotemporal correlation of wind farms, where geographically dispersed farms can experience similar weather patterns, leading to correlated outputs [2]. Accurate modeling of these dynamics is essential for assessing market power and ensuring fair competition in the market. Recent studies emphasize the crucial role of RESs in market power analysis. The increased penetration of wind and solar power significantly impacts market prices and market power, which can reduce overall market prices and a reduction in the manipulation of market power [3].

However, the variability and uncertainty associated with these energy sources necessitate sophisticated modeling approaches to capture their impact accurately on market

outcomes [4]. The Herfindahl–Hirschman Index (HHI) is a widely used measure for evaluating market concentration and assessing the potential for market power. It is calculated by summing the squares of the market shares of all firms operating within a market. A higher HHI suggests a higher level of market concentration, which can indicate a greater potential for market power [5]. Recent studies have applied this index to analyze the effects of renewable energy on market dynamics. For instance, a study in [6] examines the impact of increased wind and solar penetration on market power, finding that higher renewable penetration can reduce market concentration and mitigate market power. The study presented in [7] examines how wind energy sources might influence market outcomes and the distribution of market power. The interaction between renewable energy integration and market power is further influenced by the technical characteristics of power plants, such as production limits, ramp rates, and minimum up/down times. These factors affect how different generation technologies interact in the market, influencing overall market dynamics and the potential for market power [8]. The authors in [9] assess the market power of monopolistic energy storage operators, showing how they can manipulate electricity supply and demand to influence market prices. They conclude that careful market design is needed to prevent such abuse. This aligns with the present study, as both highlight the growing complexity of market power in systems integrating RESs and storage systems. In [10], the impact of market power discrepancies between supply chain partners on firm financial performance is studied, concluding that significant power imbalances can harm the weaker partners and reduce overall market efficiency. Unequal market power distribution is a key issue in energy markets, especially with the integration of RESs. The authors in [10] highlight the critical challenge of managing power imbalances to ensure fair competition and optimal performance in markets undergoing structural changes. In [11], the impact of increasing wind power on Nordic electricity markets is examined, revealing a shift from day-ahead to intraday and regulating power markets. It finds that wind and demand forecast errors significantly affect price spreads, with wind forecast errors becoming more influential over time. The study highlights the growing importance of closer-to-real-time markets for trading and price discovery. The authors in [12] investigate how diverse generation technologies impact electricity market structures. They show that incorporating a range of generation technologies is crucial for optimizing market competitiveness and efficiency. By evaluating different generation mixes, the study finds that a balanced mix of technologies among market participants enhances the effectiveness of forward contracts and reduces market power.

The gaps in previous research that this paper addresses are as follows: Existing studies have primarily concentrated on the technical and economic efficiency of integrating RESs such as wind and solar, with insufficient attention to their impact on market power dynamics. Many studies also neglect the spatiotemporal correlations in renewable generation, which are essential for accurate modeling. Additionally, the effects of different ownership structures on market power, especially with increasing renewable penetration, have not been thoroughly explored. Scenario-based analysis is rarely used in market power studies, and detailed operational characteristics of generation units are often poorly integrated into simulations. By addressing these gaps, the paper aims to provide a more comprehensive understanding of how renewable energy affects market power, which is vital for creating more fair and efficient electricity markets. Moreover, the market concentration index used in this paper operates independently of competitors' pricing strategies, allowing its application even without detailed information on unit production costs or pricing strategies of participants.

This paper aims to investigate the impact of wind and solar power generation on structural market power. By modeling the technical characteristics of power plants and incorporating spatiotemporal correlations of wind power generation using real data, we represent the uncertainty of renewable power through a set of scenarios. The analysis explores the effects of different levels of wind penetration on market power. The simulation results using a modified PJM five-bus system demonstrate the effectiveness of the

developed method. This study contributes to the existing literature by providing insights into the short-term effects of renewable energy integration on market power, highlighting the importance of considering both structural and behavioral aspects in market power analysis. To accomplish this goal, a simulation of the day-ahead market is conducted. This simulation incorporates the technological characteristics of thermal power plants, including their maximum and minimum production capacities, ramping rates, and minimum operational and downtime periods. Additionally, solar generation and wind production uncertainty are modeled by considering the spatiotemporal correlation among wind farms using actual data for a set of scenarios. The effects of correlation and penetration levels of wind generation on potential market power are analyzed. The key contributions of this paper are as follows:

- **Market Power Analysis in Renewable-Dominated Markets:** The paper presents a novel analysis of market power in short-term electricity markets with significant RES integration. Compared to existing research, this study stands out by incorporating spatiotemporal correlations in wind power generation. Studies such as [6,7] examine the impact of wind and solar penetration on market power but lack the detailed modeling of spatiotemporal correlations that this paper provides. By leveraging real-world data, the analysis here enhances the accuracy of renewable generation modeling, addressing a gap often left unaddressed in previous works. The spatiotemporal correlation is particularly crucial because geographically dispersed wind farms can experience similar weather patterns, leading to correlated outputs, which is not fully explored in existing studies.
- **Spatiotemporal Correlation of Wind Generation:** While the importance of spatial and temporal correlations in wind farms has been discussed in previous studies [2], the focus has generally been on energy production variability rather than its impact on market power indices. Our work expands this by integrating these correlations directly into market power metrics, specifically the HHI, showing how variability in wind generation influences market concentration. The study in [2] does not explore the direct implications of these correlations on competition metrics, which this paper successfully addresses.
- **Scenario-Based Uncertainty Representation:** The application of a scenario-based uncertainty model, built upon methods such as FUZZY-ARIMA and fast-forward scenario reduction (FFSR), provides a sophisticated approach to handling renewable energy uncertainties. Existing studies such as [13] employ similar techniques for wind power forecasting, but few integrate these methods into market power simulations, especially to the extent of analyzing ownership structures and different wind penetration levels. This contribution allows for a more comprehensive understanding of how uncertainty shapes market outcomes, as discussed in [4,13], but with a deeper focus on market concentration metrics.
- **Integration of Operational Constraints:** The consideration of technical and operational constraints (e.g., ramp-up/down rates, minimum up/down times) of power plants in the market simulation offers a more realistic portrayal of market dynamics. While the authors in [14] incorporate these constraints, this paper uniquely ties them to market concentration analysis in renewable-penetrated markets, which is relatively novel.

Overall, this paper not only addresses gaps in market power analysis with RES integration but also provides a robust framework for future research in scenario-based market simulations under varying ownership and operational conditions. The structure of the paper is organized as follows: Section 2 presents the modeling of the concentration boundary problem. The scenario generation technique and its implementation are given in Section 3. In Section 4, the simulation results and discussion are presented. Section 5 summarizes the paper and provides concluding remarks and future works.

2. Problem Statement

The concentration boundary problem aims to both minimize and maximize the Herfindahl–Hirschman Index (HHI) while adhering to the operational constraints of the market clearing problem [15]. Taking into account the technical characteristics of power plants, this problem can be reformulated as a mixed-integer linear programming (MILP) problem. Solving this MILP provides an interval for the HHI, which is useful for assessing market competitiveness [16]. The HHI ranges from zero, representing perfect competition, to 10,000, indicating a monopoly. It measures market concentration by summing the squares of the market shares of all firms.

In this model, thermal power plants are characterized by technical parameters such as minimum up and down times and ramp rates, while wind and solar power generation are included through their production constraints.

2.1. Problem Formulation

Concentration boundary problems are formulated to determine the minimum and maximum values of the HHI, considering the technical characteristics of the power plants as outlined below:

$$HHI : 10,000 \times \sum_h^{NH} \sum_{f \in \Omega^F} MSH_{fh}^2 \quad (1)$$

Subject to

$$\sum_{i \in \Omega_b^G} (P_{ih}^T + P_{ih}^W + P_{ih}^S) + \sum_{(n,b) \in \Omega^L} P_{nb,h}^L - \sum_{(b,m) \in \Omega^L} P_{bm,h}^L = P_{bh}^D, \quad \forall b \in \Omega^B, \forall h \quad (2)$$

$$P_{mn,h}^L = b_{mn}(\Theta_{mh} - \Theta_{nh}), \quad \forall (m,n) \in \Omega^L, \forall h \quad (3)$$

$$-\bar{P}_{mn}^L \leq P_{mn,h}^L \leq \bar{P}_{mn}^L, \quad \forall (m,n) \in \Omega^L, \forall h \quad (4)$$

$$-\pi \leq \Theta_{bh} \leq \pi, \quad \forall b \in \Omega^B, \forall h \quad (5)$$

$$\Theta_{bh} = 0, \quad b : \text{reference bus}, \forall h \quad (6)$$

$$n_{ih} \underline{P}_{ih}^T \leq P_{ih}^T \leq \bar{P}_{ih}^T n_{ih}, \quad \forall i \in \Omega^T, \forall h \quad (7)$$

$$0 \leq P_{ih}^W \leq \bar{P}_{ih}^W, \quad \forall i \in \Omega^W, \forall h \quad (8)$$

$$0 \leq P_{ih}^S \leq \bar{P}_{ih}^S, \quad \forall i \in \Omega^S, \forall h \quad (9)$$

$$P_{i,h+1}^T - P_{i,h}^T \leq RU_i, \quad \forall i \in \Omega^T, h < NH \quad (10)$$

$$P_{ih}^T - P_{i,h+1}^T \leq RD_i, \quad \forall i \in \Omega^T, h < NH \quad (11)$$

$$\sum_{h=1}^{NH_i^{ON}} n_{ih} = NH_i^{ON}, \quad \forall i \in \Omega^T \quad (12)$$

$$MUT_i(n_{ih} - n_{i,h-1}) \leq \sum_{t=h}^{MUT_i+h-1} n_{i,t}, \quad \forall i \in \Omega^T, h = NH_i^{ON} + 1, \dots, NH - MUT_i + 1 \quad (13)$$

$$(NH - h + 1)(n_{i,h} - n_{i,h-1}) \leq \sum_{t=h}^{NH} n_{i,t}, \quad \forall i \in \Omega^T, h = NH - MUT_i + 2, \dots, NH \quad (14)$$

$$\sum_{h=1}^{NH_i^{OF}} n_{i,h} = 0, \quad \forall i \in \Omega^T \quad (15)$$

$$MDT_i(n_{i,h-1} - n_{i,h}) \leq \sum_{t=h}^{MDT_i+h-1} (1 - n_{i,t}), \forall i \in \Omega^T, h = NH_i^{OF} + 1, \dots, NH - MDT_i + 1 \quad (16)$$

$$(NH - h + 1)(n_{i,h-1} - n_{i,h}) \leq \sum_{t=h}^{NH} (1 - n_{i,t}) \quad \forall i \in \Omega^T, h = NH - MDT_i + 2, \dots, NH \quad (17)$$

$$MSH_{fh} = \frac{\sum_{i \in \Omega^F} (P_{i,h}^T + P_{i,h}^W + P_{i,h}^S)}{\sum_{b \in \Omega^B} P_{b,h}^D}, \forall f \in \Omega^F, \forall h \quad (18)$$

The objective function (1) represents the HHI for the day-ahead market. Constraint (2) ensures that generation and load are balanced at each bus every hour. Constraint (3) calculates line flows, which are constrained by their capacity as specified in constraint (4). Constraint (5) sets limits on the voltage angles at each bus, while equality (6) fixes the voltage angle of the reference bus at zero. Constraint (7) imposes upper and lower limits on the power production of each generating unit based on its on/off status. Constraints (8) and (9) restrict wind and solar power production to not exceed the available resources from each wind and solar farm, respectively. Constraints (10) and (11) limit the ramp-up and ramp-down rates for changes in thermal power production on an hourly basis.

Equality (12) enforces the minimum up-time requirement for thermal units that were started the previous day and must remain online for a specified minimum period on the current day. Constraint (13) checks the feasibility of meeting this minimum up-time requirement across different time intervals. Constraint (14) allows thermal units to be started and operated for the remaining hours of the day if their minimum up-time exceeds the remaining hours. Constraints (15)–(17) address the minimum downtime requirements for thermal generating units. Finally, constraint (18) calculates the hourly share of production for each owner.

Both the minimum and maximum value problems are initially formulated as Mixed-Integer Quadratic Programming (MIQP) problems but are transformed into Mixed-Integer Linear Programming (MILP) problems for deriving the solution.

2.2. The Proposed MILP Model

The objective function of the concentration boundary is linearized by the method proposed in [17] as follows:

$$\text{Minimize/Maximize } 10,000 \times \sum_h \left[\sum_{f \in \Omega^F} \left(\sum_j \left(\beta_j ms_{fj,h} + x_{fj,h} \alpha_j^2 \right) \right) \right] \quad (19)$$

Subject to:

$$\text{Constraints (7 – 22)} \quad (20)$$

$$\sum_j x_{fj,h} = 1, \forall f \in \Omega^F, \forall h \quad (21)$$

$$0 \leq ms_{fj,h} \leq x_{fj,h} \Delta_j, \forall f \in \Omega^F, \forall j, \forall h \quad (22)$$

$$\frac{\sum_{i \in \Omega^F} (P_{i,h}^T + P_{i,h}^W + P_{i,h}^S)}{\sum_{b \in \Omega^B} P_{b,h}^D} = \sum_j (ms_{fj,h} + x_{fj,h} \alpha_j), \quad \forall f \in \Omega^F, \forall h \quad (23)$$

$$x_{fj} \in \{0, 1\}, \forall f, j \quad (24)$$

where ms_{fj} and x_{fj} are continuous and binary variables corresponding to segment j of the power production by owner f ; β_j and α_j are parameters determining the slope of an approximated piecewise linear function and lower bound of production at segment j ; and Δ_j is the length of the production segment j . The objective function (19) to be

minimized/maximized is the linearized HHI in (1). Constraint (20) includes the operating constraints of the market clearing problem. Constraint (21) states that for each generation, one binary variable called “active” is equal to one, while the remaining binary variables are zero. Constraint (22) limits the production at each segment by an equalized upper bound. Constraint (23) defines the production by each generation owner as a linear function of the production at the segment corresponding to the active binary variable. Constraint (24) defines binary variables used for linearizing the objective function.

3. Scenario Generation

Wind energy is a renewable and clean energy source, yet its output is inherently variable. To account for the uncertainty in wind farm production, considering the spatiotemporal correlation of actual data, a set of scenarios is implemented. This scenario generation process can be readily extended to generate correlated scenarios for multiple random variables of wind power production.

3.1. Scenario Generation Technique

To model the uncertainty of wind power generation, the FUZZY-ARIMA combined approach [13,18,19] is used, and for modeling the correlation of wind farms, the proposed method in [14] is deployed in this paper. The implementation methodology is as follows:

1. Wind power generation is dependent on the wind speed. To estimate the wind power generation function $(p^{w,fuzzy})$, fuzzy modeling and the historical data corresponding to the wind speed and wind power generation of the farm are incorporated. Fuzzy modeling is designed based on the proposed clustering method in [20].
2. The residual error is determined by measuring the discrepancy between the actual wind power data and the values predicted by the estimated function.

$$e^w = p^{w,real} - \{p^{w,fuzzy}\} \quad (25)$$

3. The empirical cumulative distribution function F for the residual error is calculated. This function is then combined with the standard normal cumulative distribution function to map the calculated error onto a normalized scale.

$$e_N^w = \psi_N^{-1}(F(e^w)) \quad (26)$$

4. An ARIMA model is fitted to the normalized errors. This way, hourly normal distribution functions $N(\mu_h, \sigma_h), h = 1, \dots, 24$, are forecasted for the wind power generation of each farm.
5. For the generation of correlated scenarios, it is necessary to identify the correlation between wind power generation of different farms. Hence, the wind power generation errors transferred to the normal field are divided into 24 vectors of $e_{N,h}^w, \forall h$; each one corresponds to each hour.
6. With 48 vectors of the transformed historical data from step 5, a 48×48 correlation matrix A is generated to capture the dependency structure of these 48 random variables across the day for two farms.
7. Several correlated wind scenarios, $\forall e_N^{w'}(s)_h, s$, are randomly generated through a standard multivariate normal distribution characterized by the correlation matrix A .
8. Each correlated standard wind scenario is converted into a correlated normal scenario $e_{N,h}^w, \forall h, s$ with a mean $\mu_h, \forall h$ and a standard deviation (STD) $\sigma_h, \forall h$, as described below:

$$e_{N,h}^w(s) = \mu_h + \sigma_h e_N^{w'}(s)_h, \forall h, s \quad (27)$$

9. Then, the correlated normal scenarios $e_{N,h}^w, \forall h, s$, by using the following equation are transferred to the normal domain.

$$\{e^w(s)\} = F^{-1}\left(\psi_N\left(\{e_{N,h}^w(s)\}\right)\right) \quad (28)$$

10. The value of predicted wind power scenarios is obtained from the sum of predicted power by the fuzzy model with predicted scenarios error for each farm.

$$\{p^w(s)\} = \{p^{w,fuzzy}\} + \{e^w(s)\} \quad (29)$$

The actual historical data from two wind farms were collected in Montana, America, covering the period from 1 January 2004, to 29 December 2006 [21]. These wind farms are geographically distributed approximately 19 km apart. Commercial Nordex N80/2500 KW wind turbines with a hub height of 100 m are installed at both sites [22]. The geographical information of these wind farms is given in Table 1. All wind data are measured every 10 min, and to ensure temporal compatibility, hourly averages of the wind data were calculated. Wind scenarios are generated according to the pseudocode shown in Figure 1.

Table 1. Geographic information on wind farms.

Wind Farm	Latitude [N]	Longitude [W]
1	45.33335	−104.41732
2	45.49285	−104.32595

1. Input data: Historical wind speed and power generation data for each farm
2. Estimate wind power generation function $p^{w,fuzzy}$ using fuzzy modeling.
3. Calculate residual error between the real power and the fuzzy predicted power.
4. Compute the empirical cumulative distribution function (CDF) of residual errors.
5. Normalize the residuals by mapping the empirical CDF to the standard normal distribution.
6. Fit the ARIMA model to the normalized residuals.
7. Generate correlated wind scenarios using a multivariate normal distribution based on the correlation matrix A.
8. Convert the correlated wind scenarios to normal scenarios
9. Map the normal scenarios back to the original domain using the inverse CDF.
10. Wind Power Scenario Prediction: Add the predicted scenario errors to the fuzzy model prediction.
11. Output: Return predicted wind power scenarios for each hour and farm.

Figure 1. Pseudocode for the proposed wind scenario generation process.

To implement the proposed scenario generation technique, a set of 100 correlated scenarios for wind speed is generated over 24 h using data from 25 March 2006, as shown in Figure 2. Initially, 5000 scenarios are generated with a spatiotemporal correlation for each farm. To reduce computational time, the total number of scenarios is then decreased

to 100 using a fast-forward scenario reduction (FFSR) method [23]. As shown in Figure 3, reducing the number of scenarios does not significantly change the mean and STD of wind generation. The correlation coefficient between the wind production of two farms for historical data and generated scenarios is shown in Figure 4. As can be seen, the correlation coefficients for both datasets are very similar.

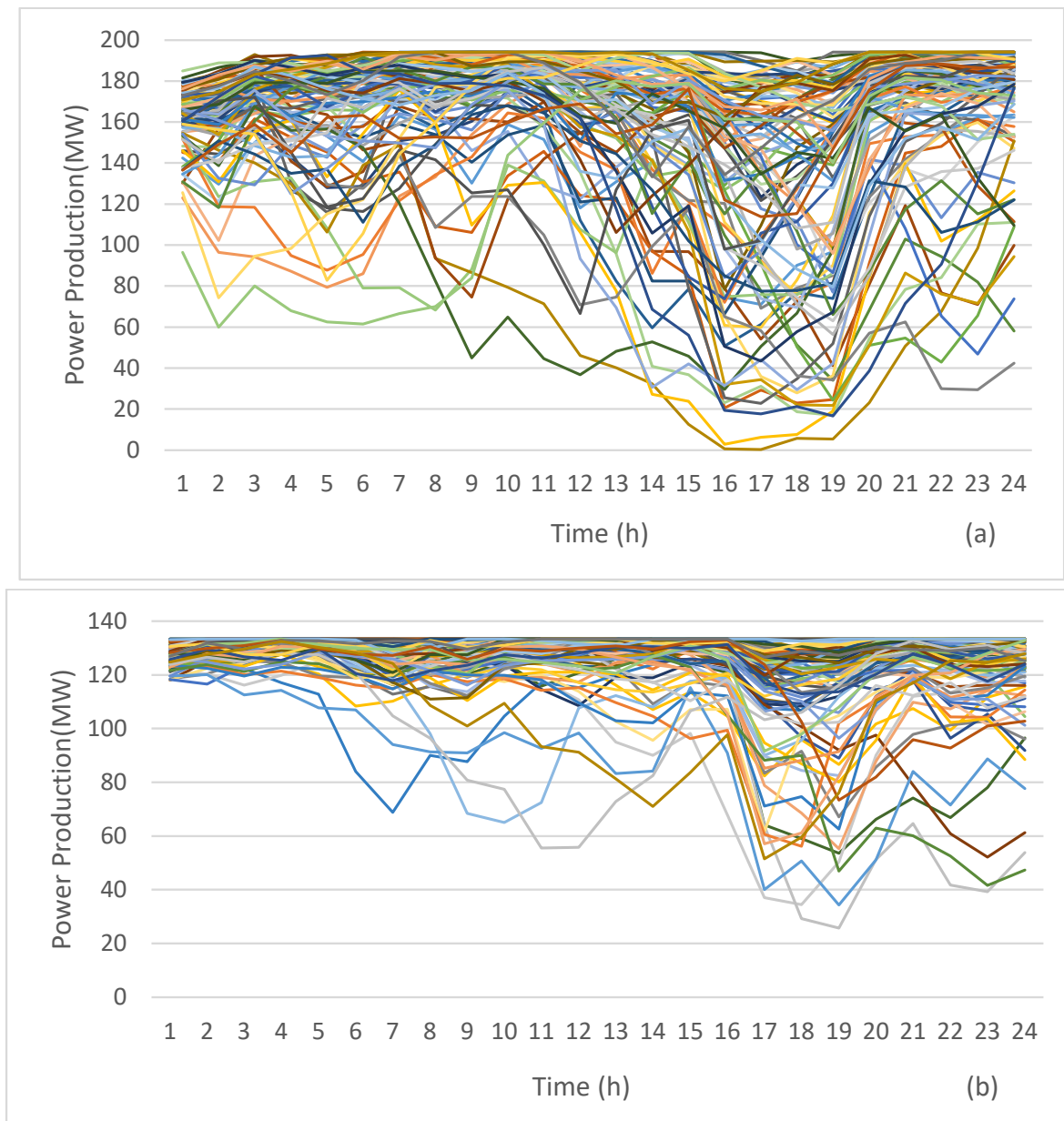


Figure 2. Set of 100 scenarios of wind generation for (a) Farm 1, (b) Farm 2.

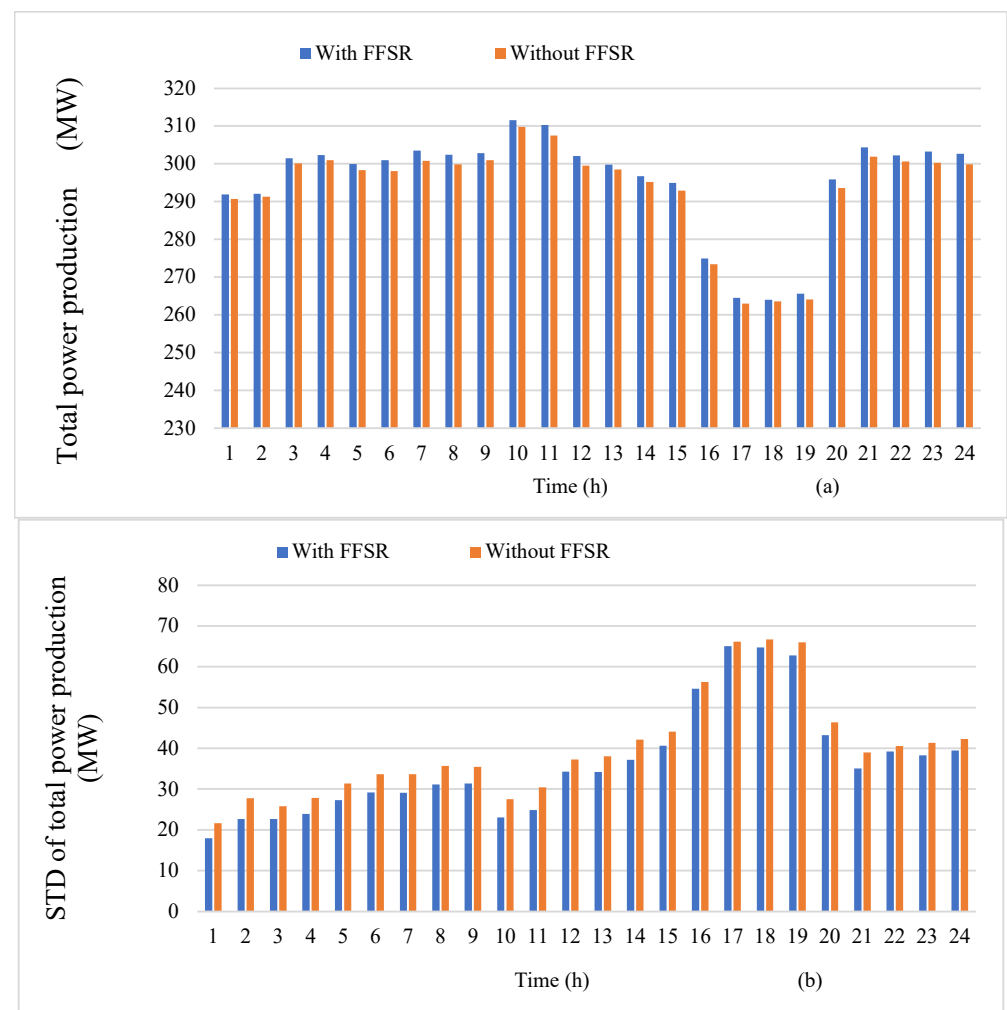


Figure 3. Mean and STD of wind generation scenarios with and without FFSR method: (a) mean, (b) STD.

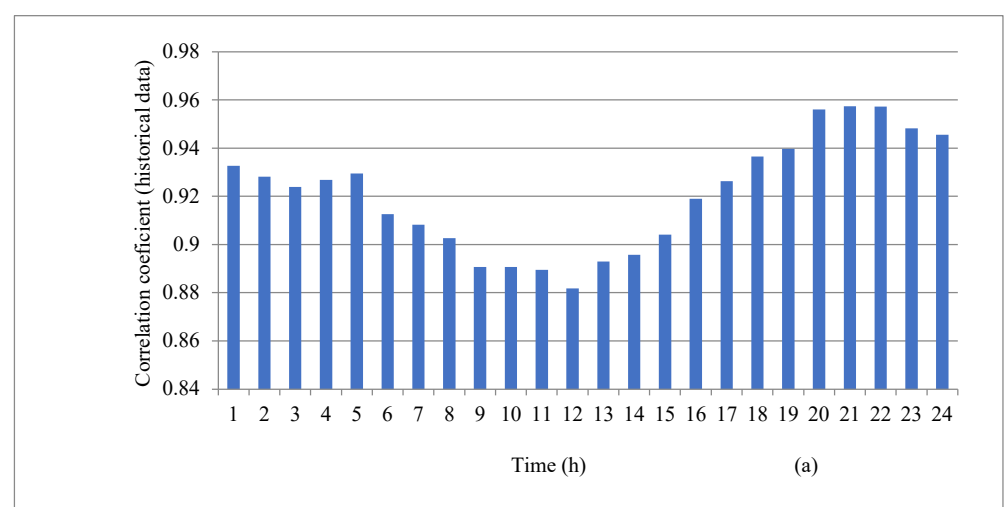


Figure 4. Cont.

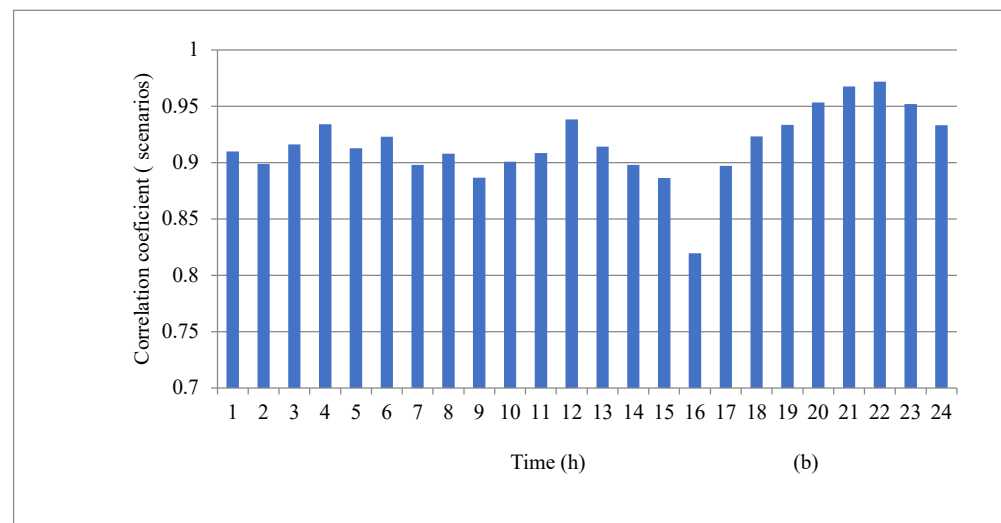


Figure 4. Correlation coefficient (a) between historical data of two farms, (b) between the generated scenarios of two farms.

3.2. Statistical Analysis Method

To examine the impact of correlated wind power production on market outcomes, a statistical analysis is conducted as follows. The steps of the analysis are presented in the pseudocode in Figure 5:

1. Generate correlated scenarios
2. Initialize $s = 1$
3. While $s \leq \text{number of scenarios}$:
 4. Retrieve the s -th scenario data for wind power production
 5. Solve the concentration boundary model with the retrieved data
 6. Save the resulting market outcomes (e.g., HHIs) for scenario s
 7. $s = s + 1$
8. End While
9. Calculate mean of market outcomes
10. Calculate STD of market outcomes

Figure 5. Pseudocode for the proposed statistical analysis method.

4. Simulation

4.1. Case Study

To evaluate the impact of the correlation between wind power productions on market power, a modified PJM five-bus system, shown in Figure 6, was used [24]. Tables 2 and 3 present the line data and the generation unit specifications, respectively. The ramp-up and ramp-down rates of thermal units are equal to their capacity per hour. Additionally, $NH_i^{ON/OF}$ is assumed to be zero, and NH is set to 24 h.

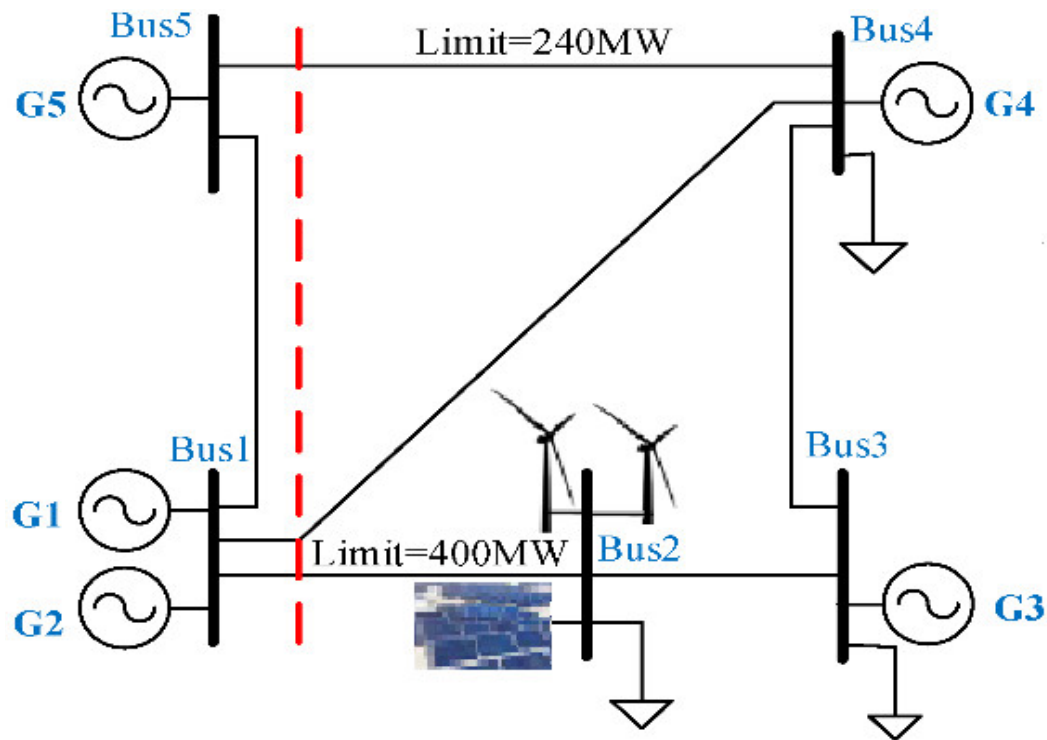


Figure 6. Single-line diagram of the 5-bus case study.

Table 2. Line data for the 5-bus case study.

Line	From Bus	To Bus	Capacity (MW)	Reactance (Ω)
1	1	2	250	0.0281
2	1	4	150	0.0304
3	1	5	400	0.0064
4	2	3	350	0.0108
5	3	4	240	0.0297
6	4	5	240	0.0297

Table 3. Generation unit data for the 5-bus case study.

Unit	Capacity (MW)	Lower/Upper Generation Limit (MW)	Min Down/Up Time (h)	Ramp-Up/Down Rates (MW/h)
1	110	22/110	3/3	100
2	100	20/100	2/2	80
3	520	104/520	1/1	400
4	200	40/200	3/3	150
5	600	120/600	5/5	500

The daily load patterns of buses 2, 3, and 4 are illustrated in Figure 7. By multiplying the values of these load profiles by 0.65, 0.85, and 1.05, we investigate the base load, average load, and peak load, respectively. Wind and solar farms are installed at bus 2, with the capacity share of the first wind farm being 59% and the second farm 41% of the total installed wind capacity. The ratio of total wind capacity to the capacity of dispatchable generating units is 22%.

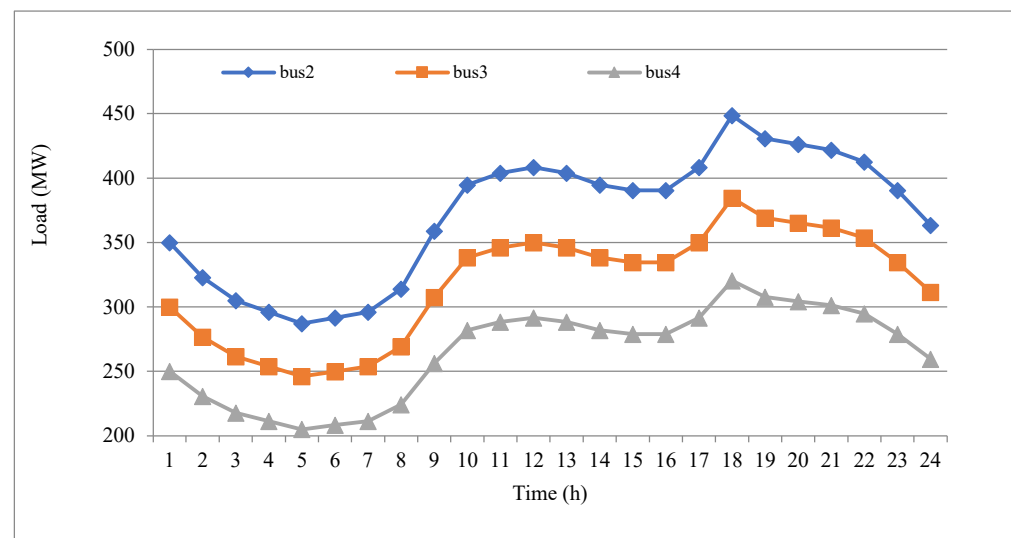


Figure 7. Daily load profiles for the 5-bus case study.

We retrieved hourly per unit (25 m^2) solar PV data from PVWatts of the National Renewable Energy Laboratory (NREL) [21]. For our simulation, we considered the power production of 100 units of PV panels. The solar power generation profile is shown in Figure 8 [25].

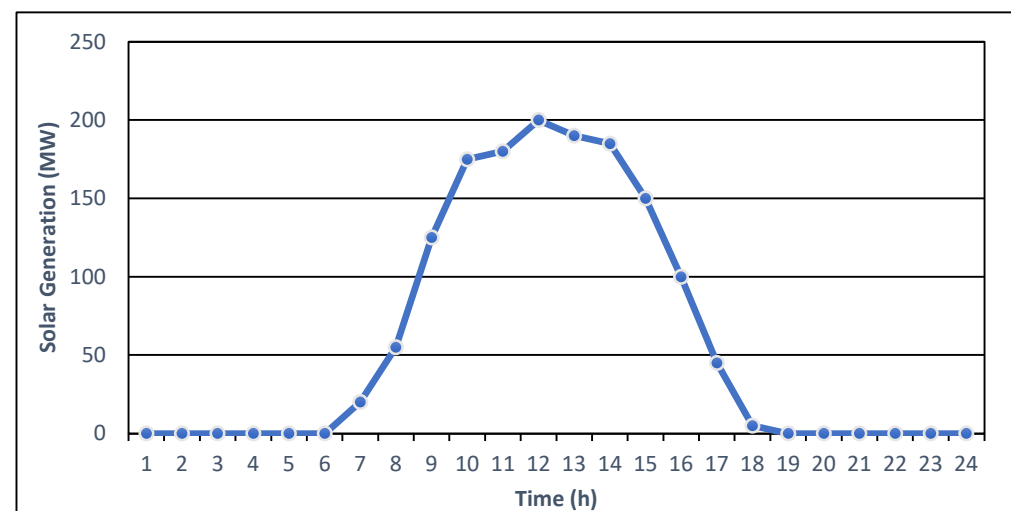


Figure 8. Daily solar power generation patterns.

4.2. Analysis of Correlation

To analyze the impact of renewable generation on structural market power, we consider a specific ownership structure involving three owners. The first owner controls production units G_1 and G_5 , the second owner manages units G_2 , G_3 , and G_4 , and the third owner focuses on renewable generations. Figures 9–14 illustrate how renewable generation and the correlation of wind farms affect the mean and STD of the HHI across the base load, average load, and peak load levels. These figures demonstrate that wind production correlation increases the STD of the HHI, while its impact on the mean HHI is minimal. According to [13], the correlation between wind production at different wind farms has a negligible impact on the mean wind power production. However, the STD of wind power production increases when the correlation between wind farms is considered. Consequently, this effect also translates to the HHI, where the mean remains largely unaffected, but the STD of the HHI increases due to the consideration of correlated wind farm outputs.

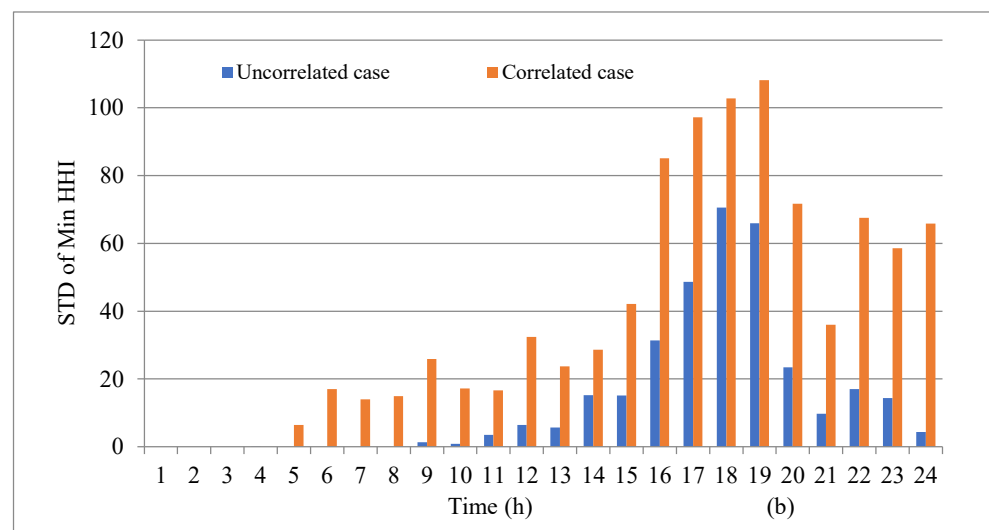
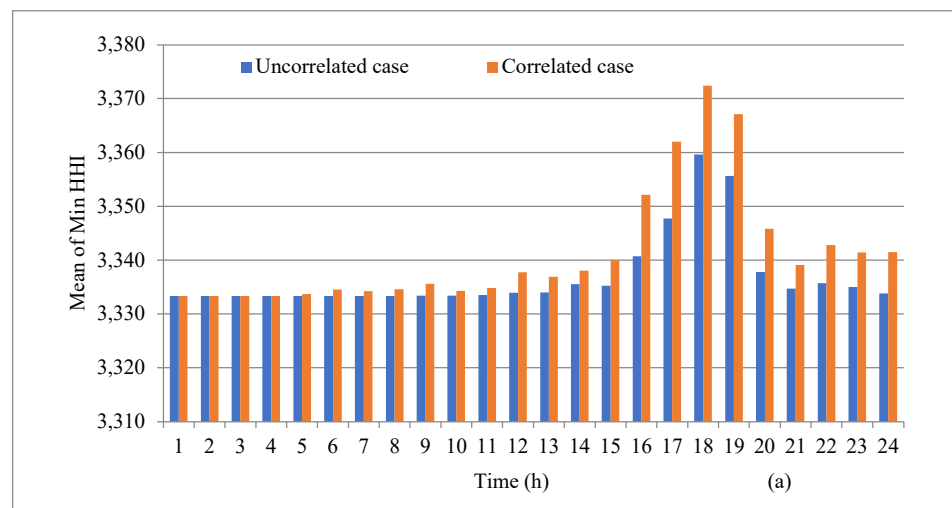


Figure 9. Minimum value of HHI with and without accounting for the correlation of wind generation in base load level for (a) mean, (b) STD.

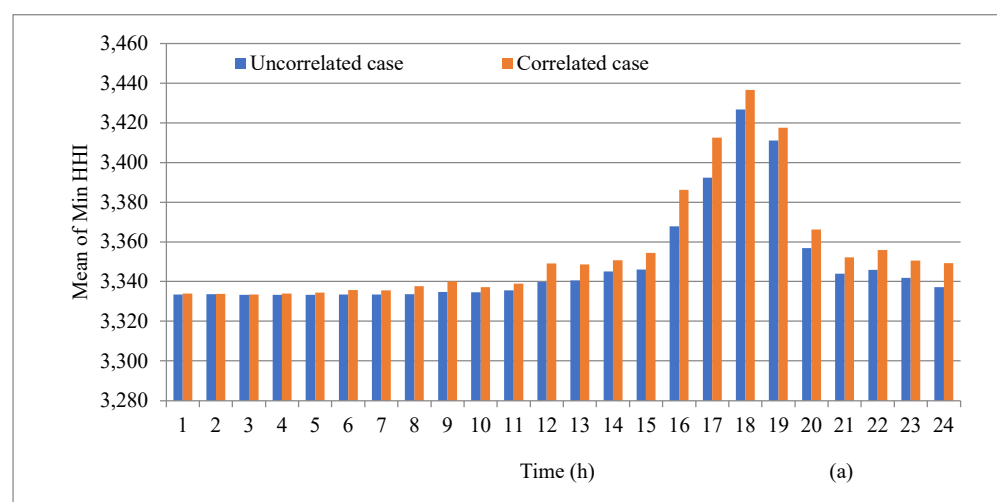


Figure 10. Cont.

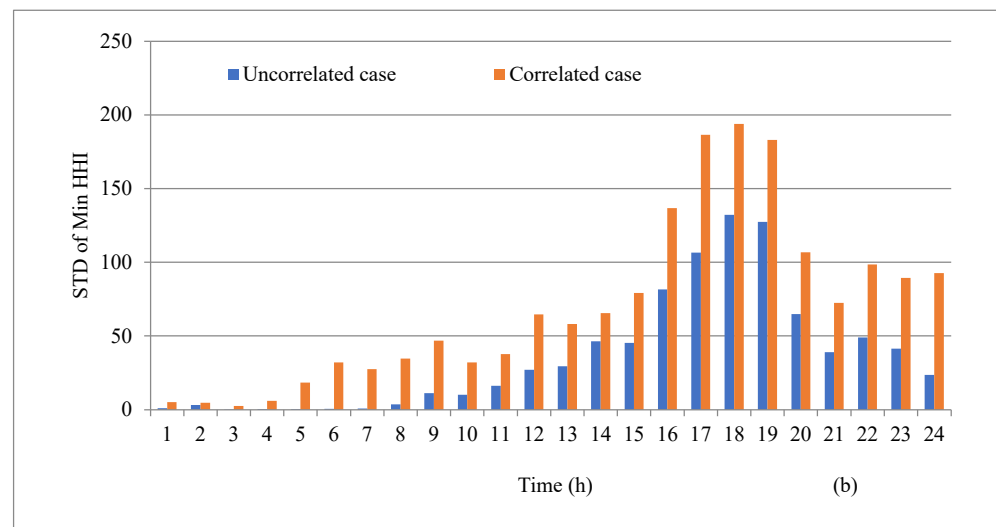


Figure 10. Minimum value of HHI with and without accounting for the correlation of wind generation in average load level for (a) mean, (b) STD.

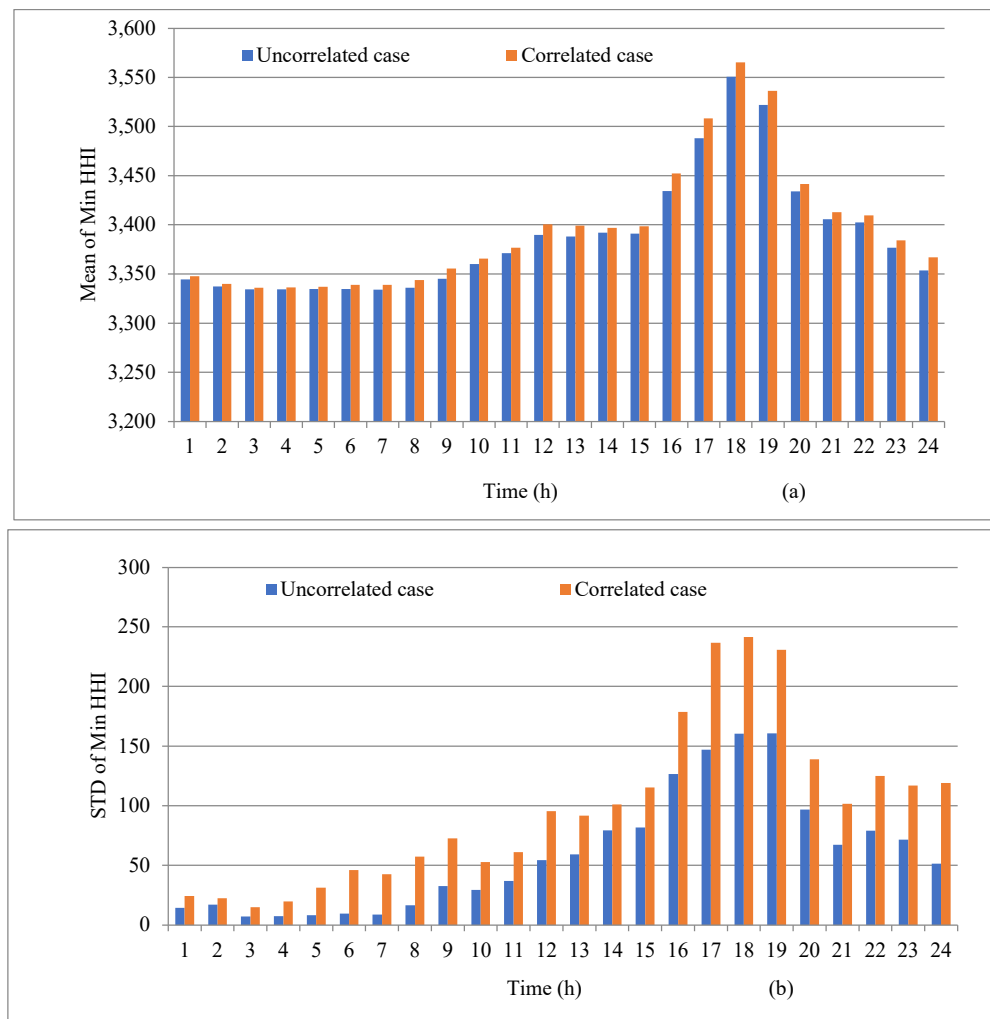


Figure 11. Minimum value of HHI with and without accounting for the correlation of wind generation in peak load level for (a) mean, (b) STD.

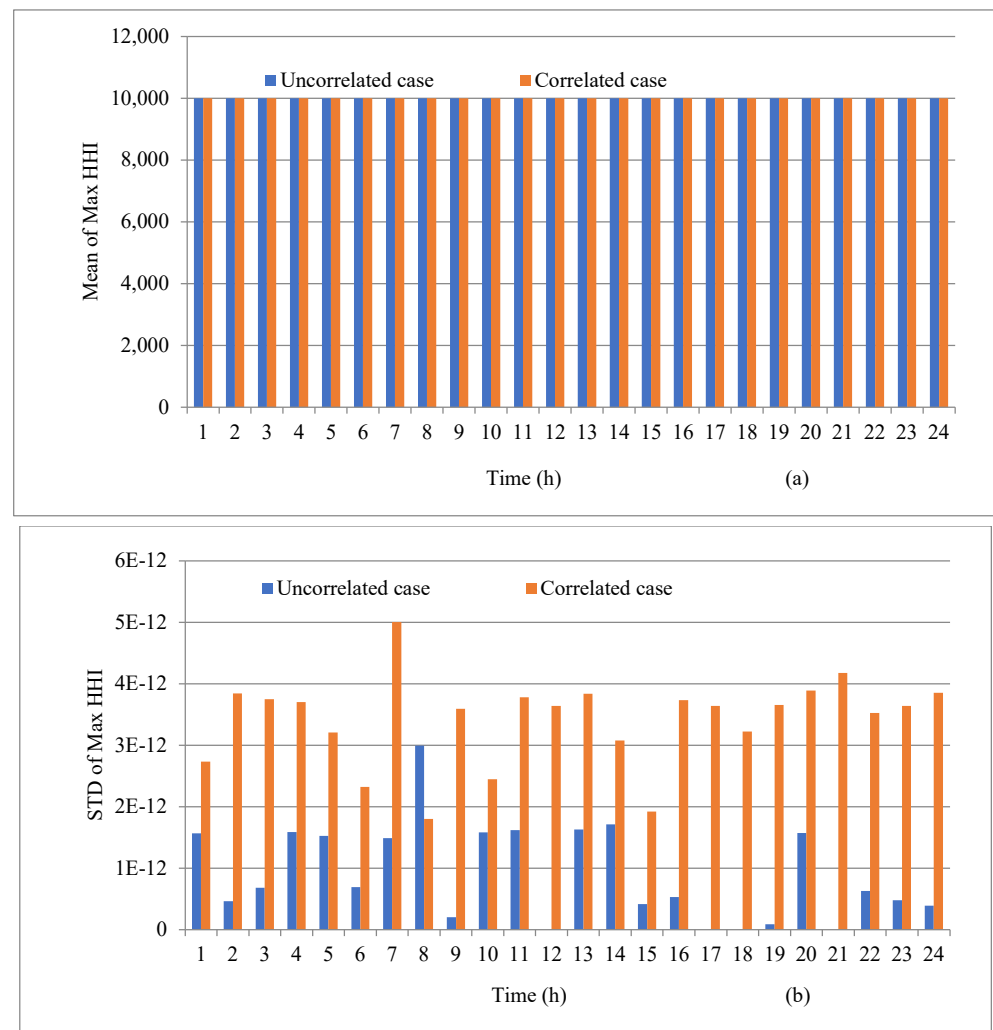


Figure 12. Maximum value of HHI with and without accounting for the correlation of wind generation in base load level for (a) mean, (b) STD.

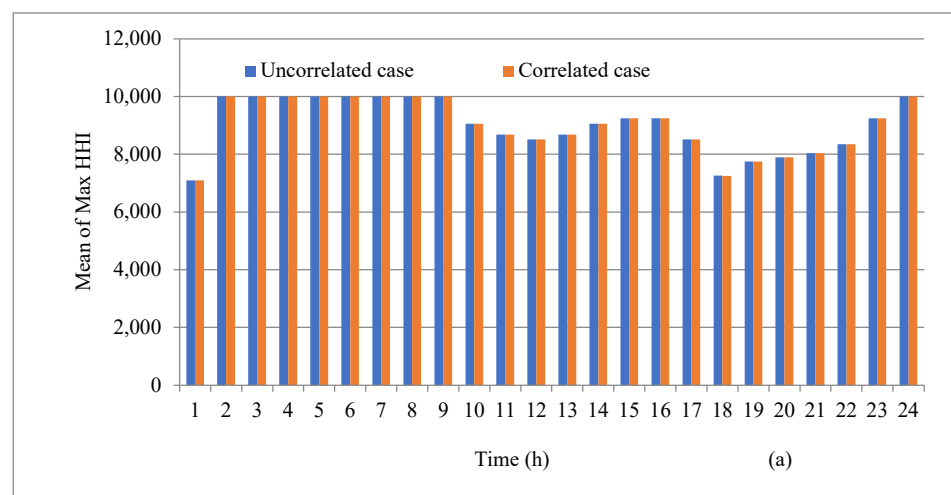


Figure 13. Cont.

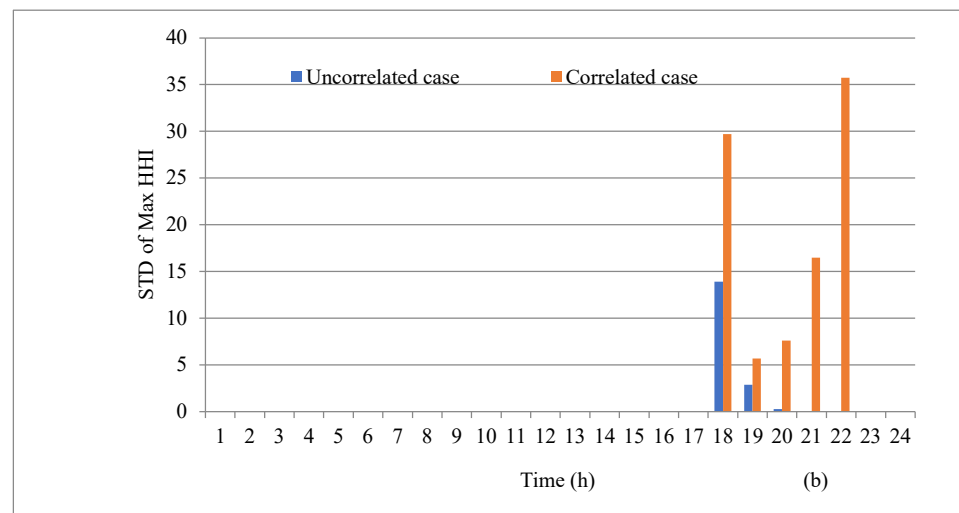


Figure 13. Maximum value of HHI with and without accounting for the correlation of wind generation in average load level for (a) mean, (b) STD.

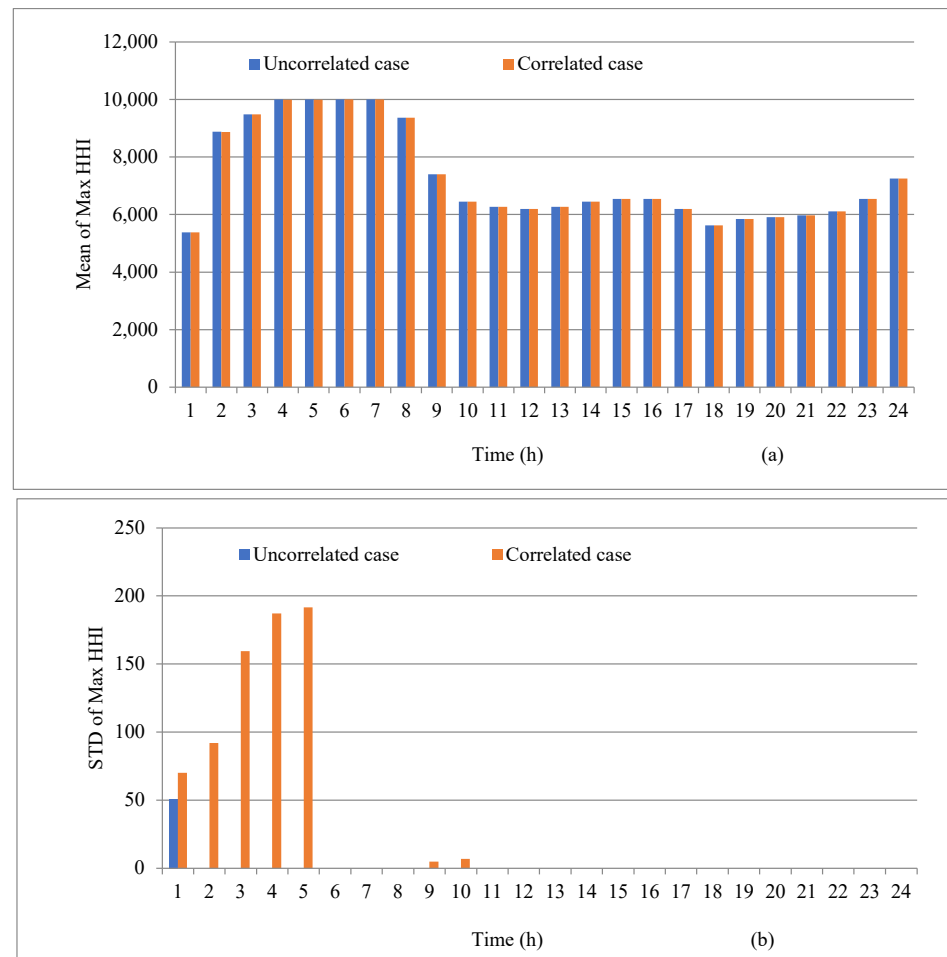


Figure 14. Maximum value of HHI with and without accounting for the correlation of wind generation in peak load level for (a) mean, (b) STD.

Specifically, accounting for wind farm correlation enhances the similarity in production changes between wind farms, thereby amplifying production volatility and subsequently affecting HHIs. The STD of the minimum HHI value rises with increasing load levels

due to production variability among larger owners with higher capacity. As changes in the HHI are relative to the shifts in production by the largest capacity owner, their STD increases accordingly.

4.3. Analysis of Wind Penetration

Figures 15 and 16 illustrate the mean and STD of the HHI at the average load level as wind penetration (WP) increases from 0% to 40%. As WP increases, it is observed that the mean minimum value of HHI decreases while the mean maximum value of HHI increases. Concurrently, the STD of both the minimum and maximum HHI values increases, indicating greater variability in market concentration. The decrease in the mean minimum value of the HHI with higher WP suggests that increased wind generation leads to a more competitive market during periods of low demand, as more generators can participate in the market. Conversely, the increase in the mean maximum value of the HHI indicates that the market concentration can become higher during periods of high demand, possibly due to the intermittent nature of wind power and the need for backup generation from fewer, larger producers. In the range of 20% to 40% WP, the changes in the mean HHI values become negligible, suggesting that the market reaches a new equilibrium where the effects of additional wind power on market concentration stabilize. However, the continuing increase in the STD of the HHI reflects heightened market volatility and competition as the system adjusts to varying levels of wind generation and load fluctuations. For WP levels exceeding 30%, the STD of the HHI drops to zero, except during peak load hours, where fluctuations in market concentration are still evident. These observations suggest that higher wind penetration levels contribute to both increased market power variability and occasional stabilization in the market concentration, depending on load conditions. The intermittent nature of wind power and its correlation with load demand are key factors driving these trends.

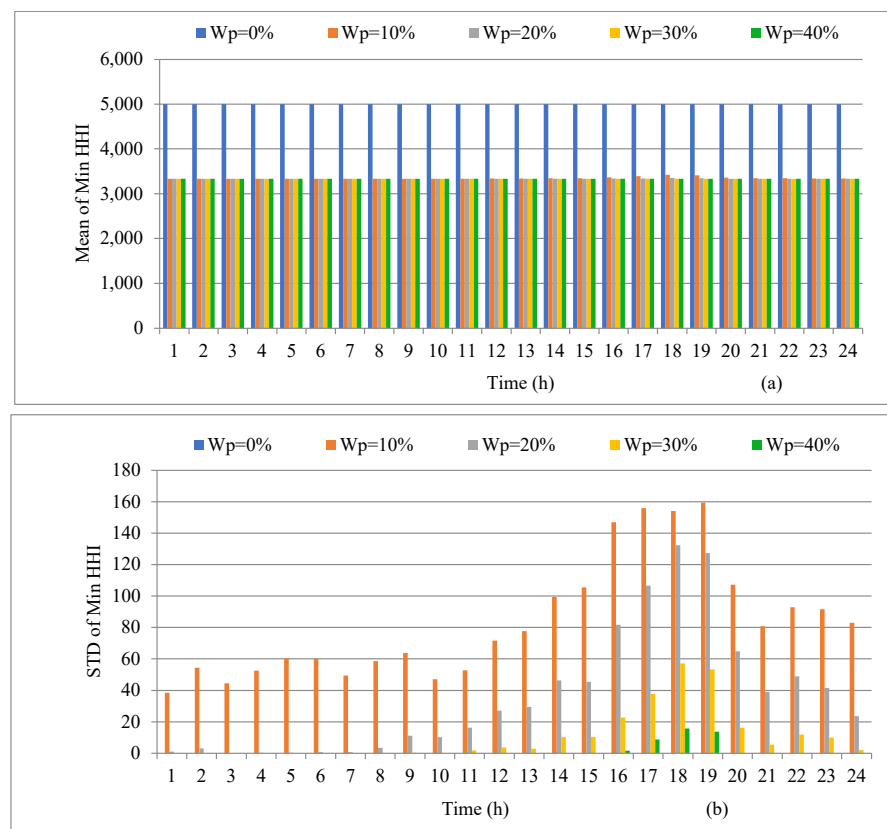


Figure 15. Minimum value of HHI with increasing level of wind penetration in average load level for (a) mean, (b) STD.



Figure 16. Maximum value of HHI with increasing level of wind penetration in average load level for (a) mean, (b) STD.

4.4. Discussion

Based on the research conducted and the simulation results obtained in Sections 4.2 and 4.3, several key lessons can be drawn that provide practical insights for decision-makers in the field of energy markets, particularly in the context of renewable energy integration.

- The integration of RESs, especially wind and solar power, has a significant effect on market dynamics. As shown in the simulations, the spatiotemporal correlation between wind farms increases the STD of the HHI, indicating greater market volatility. Decision-makers should consider these effects when evaluating market competitiveness and developing regulatory policies.
- The uncertainties in renewable energy generation, particularly due to weather dependencies, introduce significant risks in energy trading. Incorporating advanced risk management strategies, such as scenario-based planning and risk measures, can help mitigate these uncertainties and ensure stable market operations.
- As observed, higher load levels amplify fluctuations in market power due to increased variability in generation. It is important to implement policies that incentivize flexible load management and demand-side responses to reduce the impact of such fluctuations on market power.
- To create a more fair and efficient energy market, regulators and policymakers should account for the influence of renewable generation and its correlation across geographic

regions. Policies should aim to encourage diversification of energy sources and technologies to balance market power and enhance overall system stability.

These insights highlight the importance of a holistic approach to energy market design that considers the technical characteristics of RESs and their impact on market dynamics.

5. Conclusions

This paper examines the effects of the integration of renewable generation and the spatiotemporal correlation of wind farms on market power from a structural perspective over the short term. The key conclusions and policy implications derived from this study are presented below.

The correlation between wind farms leads to an increase in the STD of the HHI by 10–25%, particularly during peak load levels, driven by increased load fluctuations. However, the effect of correlation on the mean of the HHI is negligible. In addition, higher wind penetration reduces the mean minimum HHI by up to 30%, indicating increased market competition. These findings highlight important considerations for policy and market structure in the context of integrating RESs.

In future work, we would like to investigate different scenarios of load, the uncertainty of solar power generation, and the effects of the diversity of generation technologies. Additionally, we suggest employing a risk-aware approach to address these uncertainties and develop stochastic energy trading mechanisms. Specifically, we aim to investigate risk-aware trading strategies using the IGDT-based approach and the risk-averse method, as seen in recent studies on hydrogen storage and wind storage systems. This will enhance our understanding of optimal bidding strategies in the presence of renewable energy variability and inform the design of more resilient market structures.

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Nomenclature

Parameters:

b_{mn}	Susceptance value of line (m, n) .
P_{bh}^D	Power load at bus b in hour h .
$\bar{P}_{mn}^L$	Maximum flow limit of the line (m, n)
$\bar{P}_{ih}^T / \underline{P}_{ih}^T$	Upper/lower generation limit of thermal generating unit i in hour h .
NH_i^{ON} / NH_i^{OF}	Number of hours during which generating unit i must be initially online/offline due to its minimum up/down time.
MUT_i / MDT_i	Minimum up/down time of thermal generating unit i .
NH	Number of hours in the planning horizon.
RU_i / RD_i	Ramp-up/down limit for thermal generation unit i .
h	Energy exchange period (one hour).
$\bar{P}_{ih}^W$	Available power production of the i th wind farm in hour h .
$\bar{P}_{ih}^S$	Available power production of the i th solar farm in hour h .

Variables:

P_{ih}^W	Power production of the i th wind farm in hour h .
P_{ih}^S	Power production of the i th solar farm in hour h .
P_{ih}^T	Power production of thermal generating unit i in hour h .
$P_{mn,h}^L$	Power flow through line (m, n) in hour h .
Θ_{bh}	Voltage angle at bus b in hour h .
MSH_{fh}	Market share of owner f in hour h .
n_{ih}	Binary variable to show the on/off status of the i th generating unit in hour h .

Sets:

Ω^T	Set of thermal generating units.
Ω^W	Set of wind farms.
Ω^S	Set of solar farms.
Ω^B	Set of buses.
Ω^L	Set of lines.
Ω_b^G	Set of generating units located at bus b .
Ω^F	Set of owners.

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