Coalitional Aggregation of Wind Power

Enrique Baeyens, Eilyan Y. Bitar, Pramod P. Khargonekar, and Kameshwar Poolla

Abstract—This paper explores scenarios in which independent wind power producers form willing coalitions to exploit the reduction in aggregate power output variability obtainable through geographic diversity. In the setting of a two-settlement electricity market, we examine the advantage gained through optimal coalitional contract offering strategies for quantity risk reduction. We show that a group of independent wind power producers can always improve their expected profit by cooperatively offering their aggregated power. Using coalitional game theory we identify sharing mechanisms to fairly allocate the profits to coalition members. We show that the resulting coalitional game is balanced, guaranteeing that the core of the game is necessarily nonempty. In addition, we propose a profit sharing mechanism that minimizes the worst-case dissatisfaction to recover an imputation in the core. Finally, we illustrate our theoretical results with empirical studies using data from five representative wind farms in upstate New York.

Index Terms—Coalitional games, electricity markets, renewable energy integration, wind energy aggregation.

I. INTRODUCTION

W

IND and solar energy resources offer enormous potential to reduce CO₂ emissions by displacing traditional fossil fuel sources [5]. One of the primary challenges of integrating wind and solar generation lies in their inherent variability—they are intermittent, difficult to forecast, and have limited dispatchability. This increased variability presents a central challenge to the large-scale integration of renewable energy into the electric grid [7], [9], [10], [14].

It is widely accepted that combining spatially diverse wind energy resources reduces the aggregate power variability [7], [14]. A recent report by NREL [7] claims: “Both variability and uncertainty of aggregate wind decrease [...] with more wind and larger geographic areas,” which is derived from the tendency of wind speed at different geographic locations to decorrelate with increasing spatial separation. The variability of renewable energy sources can have significant impacts on power system operations, reliability and efficiency. With increasing penetration of renewables, these impacts must be properly managed through careful generation and transmission planning and novel system and market operations.

In this paper, we analyze and quantify the financial benefit of wind power aggregation through coalitional bidding in a competitive two-settlement market setting. We analyze the scenario in which a group of independent wind power producers (WPPs) willingly form coalitions to jointly offer their aggregate output as a single entity in forward energy markets. As the realized energy deviations from contracts offered ex-ante are penalized, the coalition can leverage the complementarity between its constitutive members’ production levels to mitigate its quantity risk. This approach increases the aggregate coalition profit. How should this aggregate profit be fairly allocated among the coalition members to ensure stability of the coalition?

We answer this question in the framework of cooperative game theory [16]. Individual wind power producers are players in the game, a coalition is some collection of players, and the grand coalition consists of all players. The value of any coalition in the game is defined as the maximum expected profit realized through a joint contract offering in a two-settlement market by the coalition. Using this framework, we first show that coalition formation always leads to an increase in expected profit. Next, we show that there always exists a payoff allocation that stabilizes the grand coalition. Further, it has been previously shown in [1] that this game is not convex. Consequently, the Shapley mechanism is not necessarily stabilizing. As an alternative to Shapley, we propose a stabilizing payoff allocation that minimizes the worst-case dissatisfaction (excess) over all coalitions.

As the value function under consideration is defined in the metric of optimal expected profit, any imputation belonging to the corresponding core represents the payment that each wind power producer should receive on average. However, the realized profits are random. To accommodate this issue, in Section IV-C we propose an ex post payoff allocation mechanism to distribute the realized profit among the coalition members. Under this allocation, the long term average payment that each member receives approaches an imputation in the core, almost surely. While distinct in its formulation and context, our work has strong connections with the classical newsboy problem [8], [12], [24]. A preliminary version of this paper was presented at the 50th IEEE CDC [1].

II. PROBLEM FORMULATION

A. Aggregate Wind Power Model

We consider a collection of N independent WPPs indexed by i ∈ N := {1, 2, . . . , N}. The wind power produced by pro-
producer $i \in \mathcal{N}$ is modeled as a scalar valued stochastic process $w_i(t) \in [0, W_i]$, where $W_i$ denotes the nameplate capacity of farm $i$. The wind power processes are defined on the time interval $[t_0, T]$ with width $T = t_f - t_0$. The cumulative distribution function (CDF) of the vector-valued random process, $w(t) = [w_1(t), \ldots, w_N(t)]^T$, at each time $t$ is denoted by

$$
\Phi(w; t) = P \{ w(t) < w \}
$$

where the inequality is taken component wise. The distribution $\Phi(w; t)$ has support on a compact subset $[0, W_i] \subseteq \mathbb{R}^N$. We denote the corresponding density function by $\phi(w; t)$.

A1) We consider a "copper plate" model in which we disregard the network structure of the power system. This key assumption is tantamount to having all wind generators connected to a common bus in the power network or equivalently, that the network is uncongested, yielding uniform locational marginal prices (LMPs) across buses.

The more general case in which wind generators connect to different buses in a capacity constrained transmission network is substantially more complicated and not addressed in this paper. The assertion that a collection of wind generators can reduce quantity risk by aggregating their outputs remains valid. However, physical power flow and line capacity constraints will complicate the economics of aggregation. One possible approach to this problem is to use the framework of financial transmission rights. These allow hedging against transmission congestion without the complications arising from the physical flow of power.

In this paper, we focus on timescales related to bulk power offerings in wholesale energy markets. As such, we do not consider detailed issues of grid interconnection requirements in terms of protection, voltage, frequency, synchronization, etc. These details depend on the nature of wind turbines, inverters, and power electronics employed and are assumed to be covered separately.

It follows from assumption A1 that the family of WPPs, $\mathcal{N}$, will face a common nodal price and can directly aggregate their injected power without regard to line capacity constraints. In such a setting, it is appropriate to explore scenarios in which individual WPPs form a willing coalition $\mathcal{S} \subseteq \mathcal{N}$ to collectively offer their aggregate power into the energy market as a single entity. We denote the aggregate power output of a coalition $\mathcal{S} \subseteq \mathcal{N}$ as

$$
w_\mathcal{S}(t) = \sum_{i \in \mathcal{S}} w_i(t).
$$

The corresponding random process is denoted by $w_\mathcal{S} = \{w_\mathcal{S}(t) \mid t \in [t_0, T]\}$. The CDF associated with the aggregate wind power output $w_\mathcal{S}(t)$ at time $t$ is defined as

$$
\Phi_\mathcal{S}(w; t) = P \{ w_\mathcal{S}(t) < w \}
$$

for a coalition $\mathcal{S}$ of size $|\mathcal{S}|$. Of primary importance is the time-averaged CDF

$$
F_\mathcal{S}(w) = \frac{1}{T} \int_{t_0}^{t_f} \Phi_\mathcal{S}(w; t')dt.
$$

Let $F_\mathcal{S}^{-1} : [0, 1] \rightarrow [0, \sum_{i \in \mathcal{S}} W_i]$ denote the associated quantile function. For any $\beta \in [0, 1]$, the $\beta$-quantile of $F_\mathcal{S}$ is given by

$$
F_\mathcal{S}^{-1}(\beta) = \inf \{ x \in [0, 1] \mid \beta \leq F_\mathcal{S}(x) \}.
$$

B. Market Model and Metrics

We consider a competitive market with a two-settlement structure [22] through which WPPs submit offers for energy. It consists of two ex-ante markets [a day-ahead (DA) forward market and a real-time (RT) spot market] and an ex-post penalty mechanism to settle uninstructed deviations from ex-ante offers. The penalty price for uninstructed deviations reflects the RT spot price of energy. Consequently, the imbalance penalty prices are assumed unknown at the close of the DA forward market and are not revealed until the RT spot market is cleared.

Let $C$ denote the constant power contract that a coalition $\mathcal{S} \subseteq \mathcal{N}$ jointly offers in a single ex-ante DA forward market, scheduled to be delivered continuously over a single time interval $[t_0, T]$. In the absence of energy storage capabilities, the wind power processes are defined as random variables, with expectations denoted by

$$
\mu_q = E[q], \quad \mu_\lambda = E[\lambda].
$$

The imbalance prices $(q, \lambda) \in \mathbb{R}_+^2$, tend to exhibit volatility and can be difficult to forecast, they are modeled as random variables, with expectations denoted by

$$
\mu_q = E[q], \quad \mu_\lambda = E[\lambda].
$$

A2) The WPPs behave as price takers. This assumption is justified, because the individual WPP capacities are assumed to be small relative to the entire market. Consequently, the forward price $p$ is assumed fixed and known.

A3) The WPPs have a zero marginal cost of production.

A4) As imbalance prices $(q, \lambda) \in \mathbb{R}_+^2$, tend to exhibit volatility and can be difficult to forecast, they are modeled as random variables, with expectations denoted by

$$
\mu_q = E[q], \quad \mu_\lambda = E[\lambda].
$$

The imbalance prices $(q, \lambda)$ are assumed to be statistically independent of the wind $w(t)$.

A5) The imbalance prices are assumed to be nonnegative, i.e., $(q, \lambda) \in \mathbb{R}_+^2$.

Operating under this market model, the profit acquired by a coalition $\mathcal{S} \subseteq \mathcal{N}$ for an offered contract $C$ on the interval $[t_0, T]$ is given by

$$
\Pi(C; w_\mathcal{S}, q, \lambda) = \int_{t_0}^{t_f} p C - q (C - w_\mathcal{S}(t))^+ - \lambda |w_\mathcal{S}(t) - C|^+ dt
$$

where $x^+ = \max\{x, 0\}, x \in \mathbb{R}$. This profit consists of the revenue derived from the ex-ante contract $C$ (first term) less the cost of the realized imbalances ex-post (second and third terms). A similar treatment can be found in [2], [4], and [11]. Clearly,
the profit as defined by (6) is random given its dependence on the random wind power process \( w_S \). We define the *expected profit* as

\[
J_S(C) = \mathbb{E} \Pi(C, w_S, q, \lambda). \quad (7)
\]

In addition to the metric of expected profit, we also define the *expected shortfall* and *surplus* relative to a contract offering \( C \) as

\[
H_S^-(C) = \mathbb{E} \int_{t_0}^{t_f} [C - w_S(t)]^+ dt
\]

\[
H_S^+(C) = \mathbb{E} \int_{t_0}^{t_f} [w_S(t) - C]^+ dt.
\]

**C. Optimal Contracts**

A *profit maximizing contract* \( C^*_S \) for a given coalition \( S \subseteq N \) is given by

\[
C^*_S = \operatorname{arg max}_{C \geq 0} J_S(C). \quad (8)
\]

The solution to this problem is explored in depth in [2]. For completeness, the main result is restated below for the important case of \( \mu_q \geq p \).

**Theorem 1 ([2]):** Define the time-averaged distribution \( F_S(w) \) as in (4). An optimal contract \( C^*_S \) is given by

\[
C^*_S = F_S^{-1}(\gamma), \quad \text{where} \quad \gamma = \frac{p + \mu_\lambda}{\mu_q + \mu_\lambda}. \quad (9)
\]

The *optimal expected profit, shortfall, and surplus* are given by

\[
\frac{J_S(C^*_S)}{T} = \mu_q \int_0^\gamma F_S^{-1}(x) dx - \mu_\lambda \int_0^1 F_S^{-1}(x) dx \quad (10)
\]

\[
H_S(C^*_S) = T \int_0^\gamma [C^*_S - F_S^{-1}(x)] dx \quad (11)
\]

\[
H_S^+(C^*_S) = T \int_0^\gamma [F_S^{-1}(x) - C^*_S] dx. \quad (12)
\]

**Remark 2 (Anti-Competitive Behavior):** In this paper, we allow for groups of wind power producers to aggregate their output cooperatively. This naturally raises issues of anti-competitive behavior. Aggregation is expected to play a significant role in managing the systemic variability of wind power. Our objective is to analyze the economic value of cooperation. Suitable regulatory mechanisms will need to be designed to ensure that such cooperation can facilitate systemic benefits from reduced variability while safe-guarding against possible market manipulation. Discussion of such regulatory mechanisms is beyond the scope of this paper.

**Remark 3 (A Noncooperative Game Formulation):** As an alternative to our cooperative game formulation, one might consider a noncooperative game in individual contract offerings, where the cost of the aggregate imbalance is allocated according to pre-specified mechanism for imbalance cost allocation. Naturally, the question arises of how to fairly allocate the cost of the aggregate imbalance to the responsible market participants. Given such an imbalance cost allocation mechanism, it is natural to ask as to whether there exists a Nash equilibrium in pure strategies for individual contract offerings. Finally, it would be of interest to characterize the efficiency loss (as compared to the cooperative solution analyzed in this paper) induced by noncooperative behavior, as measured by the price of anarchy or stability. These questions alone, provide the basis for several interesting extensions of the results presented here.

We introduce a functional \( \Psi \) that will play a pivotal role in analyzing the coalitional game associated with wind power aggregation. Let \( x = \{x(t)\mid t \in \mathbb{R}\} \) be a scalar random process taking nonnegative values on \([t_0, t_f]\) and define the functional \( \Psi(x) \) as a mapping from the space of square integrable random processes to the positive reals:

\[
\Psi(x) := \max_{C \geq 0} \mathbb{E} \Pi(C, x, q, \lambda) \quad (13)
\]

where \( \Pi \) is defined in (6).

To simplify our notation, we designate the random process \( x \) as the input argument to the functional \( \Psi \), rather than the underlying probability law on which the functional directly acts. We next establish some properties of \( \Psi \) that we will need subsequently.

**Lemma 4:** For any pair of random processes \( x = \{x(t)\mid t \in \mathbb{R}\} \) and \( y = \{y(t)\mid t \in \mathbb{R}\} \), we have

1) (positive homogeneity) \( \Psi(\alpha x) = \alpha \Psi(x), \forall \alpha \geq 0 \)

2) (superadditivity) \( \Psi(x + y) \leq \Psi(x) + \Psi(y) \)

where \( \alpha x = \{\alpha x(t)\mid t \in \mathbb{R}\} \) and \( x + y = \{x(t) + y(t)\mid t \in \mathbb{R}\} \).

**Proof:** See the Appendix.

**D. Value of Coalition Formation**

One of the objectives of this paper is to quantify the benefit (in the metrics of expected profit, shortfall, and surplus) obtainable through coalitional contract offerings. The following result demonstrates that *risk sharing* through coalition formation leads to an increase in collective profit almost surely.

**Lemma 5:** Let \( \{C_1, \ldots, C_N\} \) be a set of \( N \) individual contracts. For \( C_N = \sum_{i=1}^N C_i \) we have almost surely that

\[
\Pi(C_N, w_N, q, \lambda) \geq \sum_{i=1}^N \Pi(C_i, w_i, q, \lambda). \quad (14)
\]

**Proof:** The inequality (14) follows from sub-additivity of the function \( \cdot^+ \).

**Lemma 5** establishes that coalitional contract offerings always yield a net increase in collective profit. Intuitively, the benefit derivable from coalitional contract offerings can be attributed to the reduction of statistical dispersion from aggregation. This notion can be made precise, as the optimal expected profit was shown in [2] to depend explicitly on a measure of statistical dispersion referred to as the conditional value-at-risk (CVaR) deviation measure [17]. More precisely, for any \( \gamma \in (0, 1) \), the CVaR deviation of \( W_S \sim F_S \) is defined as

\[
\mathcal{D}_\gamma(W_S) := \mathbb{E}[W_S] - \mathbb{E}[W_S^+ | W_S \leq F_S^{-1}(\gamma)]. \quad (15)
\]

CVaR deviation essentially measures the gap between the unconditional mean and the mean in the \( \gamma \)-probability tail. Using
straightforward algebraic manipulations, one can rearrange the expressions for optimal expected profit, shortfall, and surplus in Theorem 1 to illuminate their explicit dependence on dispersion in the underlying distribution. More precisely

\[
J_S \left( C_S^* \right) - \sum_{i \in S} J_i \left( C_i^* \right) = \alpha E \left[ W_i \right] - \alpha E \left( W_S \right) 
\]

\[
H_S \left( C_S^* \right) = \gamma \left( C_S^* - E \left[ W_S \right] \right) + \gamma \Delta_S \left( W_S \right) + \delta \Delta_T \left( W_S \right)
\]

\[
H_S^* \left( C_S^* \right) = \left( 1 - \gamma \right) \left( E \left[ W_S \right] - C_S^* \right) + \gamma \Delta_S \left( W_S \right)
\]

Of interest is the net change in these metrics induced through aggregation. Let

\[
\Delta_S := \sum_{i \in S} \Delta_i \left( W_i \right) - \Delta_S \left( W_S \right)
\]

denote the reduction in dispersion induced by aggregating the production from farms in the coalition \( S \). One can readily show that \( \Delta_S \geq 0 \) for all \( S \subseteq N \). It follows that the net benefit due to aggregation is directly attributable to a reduction in dispersion as measured by CVaR. In particular

\[
J_S \left( C_S^* \right) - \sum_{i \in S} J_i \left( C_i^* \right) = \alpha I \Delta_S
\]

\[
\sum_{i \in S} \left( C_i^* - H_S \left( C_S^* \right) \right) = \gamma I \left( \Delta_S - \Delta_S \right)
\]

\[
\sum_{i \in S} H_i^+ \left( C_i^* \right) - H_S^* \left( C_S^* \right) = \gamma I \left( \Delta_S - \Delta_S \right) + \delta I \Delta_T
\]

where \( \Delta_S := C_S^* - \sum_{i \in S} C_i^* \). From (20), it is clear to see that aggregation will improve the optimal expected profit insonuch as it reduces the statistical dispersion of the aggregate output. The impact of dispersion reduction on expected optimal shortfall (21) and surplus (22) is less direct, as the net change in these metrics is also dependent on net change in the collection of contract offerings, \( \Delta_S \).

While the previous results establish that coalitional contract offerings always yield a net increase in collective profit, nàive sharing mechanisms, such as equal distribution of the profit among the participants, are not satisfactory, as certain coalition members may be capable of obtaining a greater profit by defecting and forming a smaller coalition. Thus, our primary objective is to identify payoff allocation mechanisms that stabilize the grand coalition \( N \).

We review basic concepts and results from cooperative game theory in the proceeding section. A more detailed review of the subject can be found in [13], [15], and [16].

### III. Background: Coalitional Game Theory

Game theory deals with rational behavior of economic agents in a mutually interactive setting. Cooperative (or coalitional games) [15] have been used extensively in diverse disciplines such as social science, economics, philosophy, psychology [13] and more recently in communication networks [18].

Let \( N := \{1, 2, \ldots, N\} \) denote a finite collection of players.

**Definition 6 (Coalition):** A coalition is any subset \( S \subseteq N \). The number of players in a coalition \( S \) is denoted by its cardinality, \( |S| \). The set of all possible coalitions is defined as the power set \( 2^N \) of \( N \). The grand coalition is the set of all players, \( N \).

**Definition 7 (Coalitional Game and Value):** A coalitional game is defined by a pair \( (N, \nu) \) where \( \nu : 2^N \rightarrow \mathbb{R} \) is the value function that assigns a real value to each coalition \( S \subseteq N \). Hence, the value of coalition \( S \) is given by \( \nu(S) \).

**Definition 8 (Superadditive Game):** A coalitional game \( (N, \nu) \) is superadditive if, for any pair of disjoint coalitions \( S, T \subseteq N \) with \( S \cap T = \emptyset \), we have \( \nu(S) + \nu(T) \leq \nu(S \cup T) \).

In the following, we consider coalitional games in which the value of a coalition is transferable between players in said coalition. A central question then, is how to fairly distribute the coalition value \( \nu(S) \) among all of the members of the coalition \( S \). We make this more precisely by presenting an axiomatic formulation of fairness.

**Definition 9 (Payoff Allocation):** A payoff allocation for the coalition \( S \subseteq N \) is a vector \( x \in \mathbb{R}^N \) whose entry \( x_i \) represents the payment to member \( i \in S \) (\( x_i = 0 \), \( i \not\in S \)).

1. *(Efficiency)* An allocation \( x \) is said to be efficient if \( \sum_{i \in S} x_i = \nu(S) \).
2. *(Individually rational)* An allocation is said to be individually rational if \( x_i \geq \nu \{\{i\}\} \), \( \forall i \in S \).

**Definition 10 (Imputation):** A payoff allocation \( x \) for the grand coalition \( N \) is said to be an imputation if it is simultaneously efficient and individually rational. The set of all imputations \( I \) for the game \( (N, \nu) \) is defined as follows:

\[
I := \left\{ x \in \mathbb{R}^N : \sum_{i \in N} x_i = \nu(N) : x_i \geq \nu \{\{i\}\} , \forall i \in N \right\}
\]

We next define a fundamental solution concept for coalitional games known as the core. It is analogous to the Nash equilibrium for noncooperative games [15].

**Definition 11 (The Core):** Consider a coalitional game \( (N, \nu) \) with transferable payoff. The core \( C \) is defined as the set of imputations such that no sub-coalition can obtain a payoff which is better than the sum of the members current payoffs:

\[
C := \left\{ x \in \mathbb{R}^N : \sum_{i \in N} x_i = \nu(N) : \sum_{i \in S} x_i \geq \nu(S), \forall S \subseteq N \right\}
\]

A payoff allocation \( x \in \mathbb{R}^N \) is said to be stabilizing if it belongs to the core \( C \).

#### A. Convex and Balanced Games

Games can have empty cores. Two important classes of games with nonempty cores are convex games and balanced games—the latter being a superset of the former.

**Theorem 12 ([20]):** A coalitional game has a nonempty core if it is convex—i.e., has a supermodular value function

\[
\nu(S) + \nu(T) \leq \nu(S \cup T) + \nu(S \cap T), \forall S, T \subseteq N. \quad (24)
\]

Convexity of a coalitional game is a strong condition and many real-world games are not convex. A weaker condition is balancedness of a coalitional game.

**Definition 13 (Balanced Map):** A map \( \alpha : 2^N \rightarrow [0, 1] \) is said to be balanced if for all \( i \in N \), we have \( \sum_{S \in 2^N} \alpha(S) 1\{i \in S\} = 1 \).

A balanced map provides a weight for each coalition in the game such that for each player \( i \in N \), the sum of the weights corresponding to all coalitions that contain the player \( i \) equals one.
Definition 14 (Balanced Game): A game \( \{N, v\} \) is balanced if for any balanced map \( \alpha: \sum_{S \subseteq N} \alpha(S)v(S) \leq v(N) \).

Theorem 15 (Bondareva-Shapley Theorem [3], [21]): A coalitional game has a nonempty core if and only if it is balanced.

Not every coalitional game is balanced. For such games, alternative solution concepts have been proposed. The most prominent being the Shapley value and the nucleolus.

B. Shapley Value and Nucleolus

The Shapley value offers an axiomatic approach to value allocation in a coalitional game. For a coalitional game \( \{N, v\} \), the Shapley value \( \chi_i(v) \) is a payoff to each player \( i \in N \) which satisfies five axioms:

1. (Individual rationality) \( \chi_i(v) \geq v\{i\} \) for all \( i \in N \).
2. (Efficiency) \( \sum_{i \in N} \chi_i(v) = v(N) \).
3. (Symmetry) If \( v(S \cup \{i\}) = v(S \cup \{j\}) \) for all \( S \subseteq 2^N \) such that \( S \cap \{i, j\} = \emptyset \), then \( \chi_i(v) = \chi_j(v) \).
4. (Dummy action) If \( v(S \cup \{i\}) = v(S) \) for all \( S \subseteq 2^N \), then \( \chi_i(v) = 0 \).
5. (Additivity) If \( v_1 \) and \( v_2 \) are two value functions then \( \chi_i(v_1 + v_2) = \chi_i(v_1) + \chi_i(v_2) \).

Theorem 16: Consider a coalitional game \( \{N, v\} \). An analytical expression for the corresponding Shapley value is given by

\[
\chi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{S! (N - |S| - 1)!}{N!} [v(S \cup \{i\}) - v(S)].
\]

The Shapley value \( \chi_i(v) \) can be interpreted as the expected marginal contribution of player \( i \) to the grand coalition \( N \) when player \( i \) joins in a uniformly distributed random order. The weight is the probability that player \( i \) enters right after every player in the sub-coalition \( S \).

The nucleolus of a coalitional game \( \{N, v\} \) is an imputation that minimizes the dissatisfaction of the players. Let \( x \in \mathbb{R}^N \) be an imputation associated with the coalitional game \( \{N, v\} \). The dissatisfaction of a coalition \( S \) with respect to the imputation \( x \) is measured by the excess defined as follows:

\[
e(x, S) = v(S) - \sum_{i \in S} x_i.
\]

For a given imputation \( x \), define the associated excess vector, \( \theta(x) \in \mathbb{R}^{|N|} \), as a vector whose entries are the excesses for all coalitions (excluding the grand coalition) arranged in nonincreasing order, i.e.

\[
\theta_k(x) \leq \theta_j(x) \text{ for all } i, j \in N \text{ such that } i \geq j.
\]

Let \( \Theta = \{ \theta(x) : x \in \mathcal{X} \} \) denote the set of excess vectors associated with each imputation \( x \in \mathcal{X} \) for a game \( \{N, v\} \).

Definition 17 (Lexicographic Order): Define a lexicographic order on the elements of \( \Theta \) as follows: \( \theta(x) \leq \theta(y) \) if there exists an index \( k \) in \( N \) such that for all \( i < k \), \( \theta_i(x) = \theta_i(y) \) and \( \theta_k(x) \leq \theta_k(y) \).

Definition 18 (Nucleolus): The nucleolus of the game \( \{N, v\} \) is the lexicographically minimal imputation.

Remark 19 (Relation to the Core): The nucleolus belongs to the core, if the core is nonempty, as the core is the set of all imputations with negative or zero excesses [6].

IV. MAIN RESULTS

Let \( N = \{1, \cdots, N\} \) denote the set of \( N \) wind power producers connected to a common bus in the power system. We use the concept of coalitional games to investigate the notion of willing coalition formation among wind power producers to jointly offer a contract for energy in a two-settlement market. Define \( v(S) \) as the expected profit corresponding to an optimal coalitional offer (Theorem 1) of the aggregate wind power \( w_S \) for the coalition \( S \subseteq N \):

\[
v(S) = \Psi[w_S] = \max_{C, q, \lambda} E \Pi(C, w_S, q, \lambda).
\]

The pair \( \{N, v\} \) then defines the coalitional game studied in this section.

A. Properties of the Coalitional Game

The coalitional game introduced above enjoys several structural properties which are established next.

Lemma 20 (Set of Imputations): The set of all imputations defined by the coalitional game \( \{N, v\} \) is given by

\[
\mathcal{I} = \{ x \in \mathbb{R}^N : x_i = v\{i\} + \lambda_i, \lambda_i \in \Lambda, \forall i \in N \}
\]

where \( \Lambda := \{ \lambda \in \mathbb{R}^N : \sum_{i \in N} \lambda_i = \mu T \Delta N \} \).

Theorem 22: The coalitional game \( \{N, v\} \) defined above is superadditive.

Proof: As the value function is defined as \( v(S) = \Psi[w_S] \) for all \( S \subseteq N \), the result follows directly from the superadditivity property of \( \Psi \) established in Lemma 4. More specifically, for any disjoint pair \( S, T \subseteq N \), we have

\[
v(S) + v(T) = \Psi[w_S] + \Psi[w_T] \\
\leq \Psi[w_S + w_T] \\
= v(S \cup T).
\]

Remark 23 (Positively Correlated Wind Processes): Superadditivity of the game \( \{N, v\} \) guarantees that coalition formation will never detract from the members’ expected profit in aggregate. However, in the degenerate case of perfectly positively correlated wind power process, the coalition optimal expected profit equals the sum of the individuals’ optimal expected profits.
if they were to participate in the market independently—i.e., $v(\mathcal{N}) = \sum_{i=1}^{N} v(\{i\})$.

A simple but important consequence of the superadditivity property is that wind power producers can collectively improve their expected profit by forming coalitions with other producers to jointly offer a contract for their aggregate power. Moreover, the larger the coalition the greater the improvement in the aggregate expected profit—indicating that the most profitable coalition is the grand coalition. Superadditivity, however, does not guarantee the existence of a stabilizing payoff allocation—i.e., the existence of a nonempty core. It turns out, however, that our game has a nonempty core.

**Theorem 24:** The coalitional game $(\mathcal{N}, v)$ for wind energy aggregation is balanced. Consequently, it has a nonempty core.

**Proof:** To see why this is true, let $\alpha : 2^{\mathcal{N}} \rightarrow [0, 1]$ be an arbitrary balanced map. Balancenedness of the game follows the properties of the value function established in Lemma 4:

\[
\sum_{S \in 2^{\mathcal{N}}} \alpha(S) v(S) = \sum_{S \in 2^{\mathcal{N}}} \alpha(S) \Psi[w_S] \\
= \sum_{S \in 2^{\mathcal{N}}} \Psi [\alpha(S)w_S], \quad \text{by positive homogeneity of } \Psi \\
\leq \sum_{S \in 2^{\mathcal{N}}} \alpha(S)w_S, \quad \text{by superadditivity of } \Psi \\
= \sum_{i \in \mathcal{N}} \sum_{S \in 2^{\mathcal{N}}} \alpha(S)1\{i \in S\}w_i \\
= \Psi \sum_{i \in \mathcal{N}} w_i = v(\mathcal{N}), \quad \text{by balancedness of } \alpha
\]

Thus, the game $(\mathcal{N}, v)$ is balanced and therefore the core is nonempty. ■

**B. Stable Sharing of Expected Coalition Profit**

As the coalitional game for wind energy aggregation has a nonempty core, there exists an imputation in the core that guarantees that no wind power producer can improve its expected profit by defecting from the grand coalition.

For convex games, the Shapley value provides a closed-form expression for an imputation that belongs to the core [20]. However, through a counterexample, it can be shown that our game is not convex and that the Shapley value does not necessarily belong to the core. See [1, Example 4.4] for a detailed exposition.

1) The Nucleolus and Minimizing Worst-Case Excess: A key merit of the Shapley value is its computational efficiency, given by its closed form characterization. However, as the Shapley value is not guaranteed to belong to the core of our game, we seek alternative solution concepts to obtain imputations in the core. As noted in Section III, the nucleolus is guaranteed to belong to the core for a balanced game. Recall that the nucleolus is defined as the imputation with the lexicographically minimal excess vector. Using results from [19], it follows that its computation requires the solution of $O(2^N)$ linear programs—exponential complexity in the number of players $N$. To overcome this challenge, we propose using the imputation that minimizes the worst-case excess for every coalition. More specifically, consider the imputation:

\[
e^* = \min_{x \in \mathbb{R}^N} \max_{S \subseteq \mathcal{N}} e(x, S) \text{ s.t. } \begin{cases} e(x, \mathcal{N}) = 0 \\
v(\{i\}) - x_i \leq 0, \forall i \in \mathcal{N} \end{cases}
\]

While computation of the nucleolus requires solving a large number of linear programs, the computation of the proposed imputation can be formulated as a single linear program:

\[
e^* = \min_{x \in \mathbb{R}^N} \max_{S \subseteq \mathcal{N}} e(x, S) \text{ s.t. } \begin{cases} v(S) - \sum_{i \in S} x_i - e \leq 0, \forall S \subseteq \mathcal{N} \\
v(\mathcal{N}) - \sum_{i \in \mathcal{N}} x_i = 0 \\
v(\{i\}) - x_i \leq 0, \forall i \in \mathcal{N} \end{cases}
\]

(28)

**Lemma 25:** Let $x^*$ be a feasible imputation achieving the minimal cost $e^*$ in problem (28). Then $x^*$ belongs to the core, if $e^* \leq 0$.

**Proof:** It is clear that a feasible imputation $x^*$ achieving the minimal cost $e^*$ is both individually rational and budget balanced. Moreover, if $e^* \leq 0$, we have that

\[
v(S) - \sum_{i \in S} x_i^* \leq e^* \leq 0 \quad \text{for all } S \subseteq \mathcal{N}
\]

which guarantees that no member has any incentive to defect from the grand coalition. ■

In [1, Example 4.6], an instance is depicted where an imputation minimizing the worst-case excess belongs to the core and the Shapley value does not. For a balanced coalitional game, the imputation that minimizes the worst-case excess in problem (28) always yields $e^* \leq 0$ and, similarly to the nucleolus, always belongs to the core, as the core contains all imputations with negative excess.

Since $e^* \leq 0$ in the optimization problem (28) for a balanced game, the constraints $v(\{i\}) - x_i \leq 0, \forall i \in \mathcal{N}$ are redundant and can be discarded. As a result, the worst-case excess imputation for a balanced coalitional game is obtained by solving the following linear program with $N + 1$ variables and $2^N - 1$ constraints:

\[
e^* = \min_{x \in \mathbb{R}^N, e \in \mathbb{R}} e \text{ s.t. } \begin{cases} v(S) - \sum_{i \in S} x_i - e \leq 0, \forall S \subseteq \mathcal{N} \\
v(\mathcal{N}) - \sum_{i \in \mathcal{N}} x_i = 0 \\
v(\{i\}) - x_i \leq 0, \forall i \in \mathcal{N} \end{cases}
\]

(29)

In the worst-case, a sequence of $O(2^N)$ linear programs, each of them with $N + 1$ variables have to be solved in order to compute the nucleolus [19]. This is computationally prohibitive except for a game with a very small number of players. Since we only seek a stabilizing solution for the coalitional game, the worst-case excess imputation is an acceptable solution because it requires solving a single linear program.

**C. Sharing of Realized Coalition Profit**

A key component of our game theoretic formulation $(\mathcal{N}, v)$ is the value function $v$ which corresponds to the optimal expected profit

\[
v(S) = \max_{C \subseteq \mathcal{N}} \mathbb{E}[v(C, w_S, q, \lambda)] \quad \text{for all } S \subseteq \mathcal{N}.
\]

It follows that an imputation $x^* \in \mathbb{R}^N$ represents the payment that each WPP (coalition member) should receive in expectation. Due to inherent randomness of wind power production [and imbalance prices $(q, \lambda)$], the actual realized profit for the grand coalition will vary day to day. It is certainly true that
expected optimal profit is guaranteed to be nonnegative. However, it may happen that realized optimal profit may take on negative values for certain realization of wind and imbalance prices. Consequently, there may occur a day such that certain members of the coalition have to pay for their contribution to the cost of contract imbalance. These observations lead to us to explore profit allocation mechanisms to distribute the realized profit among the coalition members ex-post. Naturally, it would be desirable that the payment to coalition members, averaged over an increasing number of days, approaches an imputation \( x^* \in \mathbb{C} \). We show how this can be done.

\[ w_N^{k}(t) \perp w_N^{j}(t), \quad q^k \perp q^j, \quad \lambda^k \perp \lambda^j \]

for all times \( t \in [t_0, t_1] \) and days \( k \neq j \).

It has been empirically observed that wind speed and price processes exhibit strong diurnal periodicity [23]. While independence does not follow readily, this empirical observation is the main justification of the cyclostationarity assumption on the distribution across days. An immediate consequence of the above assumption is that the optimal profit \((30)\), corresponding to any coalition \( S \subseteq N \), is also an iid sequence \( \{\Pi_S^k\} \):

\[ \Pi_S^k := \Pi \left( C_S^k, w_S^k, q^k, \lambda^k \right), \quad \text{where } C_S^k = P_{S}^{-1}(\gamma). \quad (30) \]

**Daily Profit Allocation Mechanism:** Let the allocation of the profit realized on day \( k \) be denoted by

\[ \theta^k = [\theta_1^k \cdots \theta_N^k]^T \in \mathbb{R}^N \]

where member \( i \) receives \( \theta_i^k \) of the realized profit on day \( k \).

**Definition 26 (Budget Balanced):** A profit allocation \( \theta^k \in \mathbb{R}^N \) is budget balanced with respect to the profit realized on day \( k \) if \( \sum_{i=1}^{N} \theta_i^k = \Pi_S^k \).

**Definition 27 (Consistency):** A mechanism for daily profit allocation \( \theta^k \) is strongly consistent with respect to a fixed allocation \( x \in \mathbb{R}^N \) if \( \frac{1}{K} \sum_{k=1}^{K} \theta_i^k \xrightarrow{a.s.} x_i \).

Consider the following naive mechanism for daily profit allocation. Let \( x^* \in \mathbb{R}^N \) be an imputation in the core \( \mathbb{C} \) for the coalitional game defined by the value function \((27)\). Given a realization of profit \( \Pi_S^k \) on day \( k \) for the grand coalition \( N \), distribute the profit among the coalition members according to the following rule:

\[ \hat{\theta}_i^k = \beta_i \Pi_N^k, \quad \text{where } \beta_i = \frac{x_i^*}{\sum_{j=1}^{N} x_j^*}. \quad (31) \]

**Theorem 28:** The naive profit allocation mechanism \((31)\) is both budget balanced and strongly consistent with respect to the corresponding imputation \( x^* \in \mathbb{C} \).

**Proof:** Since \( \sum_{i} \beta_i = 1 \), the proposed profit allocation scheme is budget balanced. On the other hand, the strong law of large numbers leads to strong consistency.

V. EMPIRICAL ANALYSIS

We now explore the practical implications of our results using spatial wind power time series data from the National Renewable Energy Laboratory (NREL) [7].

A. Data Set Description

The data set we use was created for the Eastern Wind Integration and Transmission Study conducted by AWS-Truewind with oversight from NREL. It consists of three-year-long wind speed and power time-series for 1362 simulated wind plants with a sampling period of 10 min. The wind speed time series were generated using a multi-scale physical model initiated with inputs from the NCEP/NCAR Global Reanalysis data set. The spatial granularity of the output is on the order of two kilometers. Finally, wind speed was converted to power output using a composite turbine output curve. We refer the reader to [7] for further details.

We focus our attention on five wind farms (indexed \( i \in \{1, \cdots, 5\} \)) located in New York State, whose approximate locations are shown in Fig. 1. These were chosen because their spatial proximity permits participation in a common market managed by the New York Independent System Operator (NYISO). We work with wind power time series of length \( M = 92 \) days—spanning 2006.03.01 to 2006.05.31. Let \( w_i(k), \quad (k = 1, \cdots, DM) \), denote the average wind power produced on the discrete time interval \( k \) of length 10 min, and \( D = 144 \) denote the sample numbers in a day.

B. Methodology

**Empirical distributions:** For each coalition \( S \subseteq \{1, \cdots, 5\} \), we construct an empirical distribution \( \hat{\Phi}_S(w; k) \) to approximate the underlying distribution \((3)\) of the average power production on the interval \( k \) as follows. First, we construct a time series (indexed by days \( m \))

\[ z_S^{(k)}(m) = \sum_{i \in S} w_i(k + (m - 1)D), \quad \text{for } m = 1, \cdots, M \]

to represent the wind power produced on a given interval \( k \) for each day \( m \). Using this modified time series, we construct the empirical distribution as

\[ \hat{\Phi}_S(w; k) = \frac{1}{M} \sum_{m=1}^{M} 1_{\{1, \cdots, w_i\}} \left( z_S^{(k)}(m) \right). \quad (32) \]

Assuming the underlying wind power process to be 1) first-order cyclostationary in the strict sense with diurnal periodicity.

Fig. 1. Location of the five wind farms in New York state.
and 2) independent across days, using the strong law of large numbers, it can be shown that $\Phi_{S}(w; k)$ is consistent with respect to the underlying data generating distribution (3). Moreover, time-averaged empirical distributions approximating (4) can be easily formed by averaging (32) over intervals of length one hour. Fig. 2 shows representative time-averaged distributions for individual wind farms and the grand coalition for two different hours of the day. Notice that the expected power production is larger at night (hour 5) than at mid-day (hour 18).

In order to measure the extent to which spatial decorrelation between wind farms improves the profitability of coalition formation, we compute the time varying correlation coefficients between each pair of wind farms as

$$\hat{\rho}_{ij}(k) = \frac{\sigma_{ij}(k)}{\sqrt{\sigma_{ii}(k)\sigma_{jj}(k)}}$$  (33)

where $\sigma_{ij}(k)$ denotes the sample covariance between $w_{i}(k)$ and $w_{j}(k)$. Fig. 3 shows the degree of correlation between the wind farms for two different hours in the day (i.e., hours 5 and 18). The degree of correlation is represented as a continuous gradient between black ($\rho = 0$) and white ($\rho = 1$). Notice from Fig. 3 that positive correlation between the different wind power processes is larger during mid-day (e.g., hour 18) than at night (e.g., hour 5). From Fig. 2 we observe that the attenuation of statistical dispersion due to aggregation is more pronounced during hour 5 than hour 18. Negative correlation between wind farms was not observed for any hour of the day in our empirical analysis. Fig. 4 shows the time-varying empirical correlation coefficient for all two-member coalitions $\{i, j\}$, $i \neq j$. From both Figs. 3 and 4, we see that increased spatial separation between wind farms generally decreases the correlation between their outputs. For instance, sites with the greatest spatial separation (i.e., $\{1,2\}, \{2,4\}, \{3,4\}$) exhibit the weakest correlation during both hours 5 and 18.

**Market parameters:** Using the empirical time-averaged distributions, we compute profit maximizing contracts and the corresponding expected profit on hour-long intervals for each possible coalition. We consider three different price penalty ratios $\gamma = (p/\mu_{k}) \in \{0.25, 0.50, 0.75\}$ with the forward price $p$ being normalized to one. Note that we ignore surplus penalties (i.e., $\mu_{k} = 0$), as we have assumed the wind farms to have curtailment capability. Imputations in the core are obtained by solving the LP outlined in (28). Fig. 6 shows the resulting imputations across different hours and price penalty ratios $\gamma$.

**C. Discussion**

From Figs. 2 and 3, we see that spatial decorrelation between wind farms leads to a reduction in statistical dispersion of the aggregated wind power. This should lead to an increase in expected profit. This relationship is made precise in (16), which shows that the increase in expected profit attributable to coalition formation depends exclusively on the reduction in statistical dispersion [as measured by CVaR deviation (15)]. To quantify the effect of decorrelation on profit increase, we plot in Fig. 5 the percentage profit increase for all possible two-member coalitions $\{i, j\}$ as a function of the empirical correlation $\hat{\rho}_{ij}$. From this figure, it is evident that the financial benefit derivable from coalitional contract offerings generally increases with reduced correlation between sites. Notice also that the marginal
Fig. 5. Scatter plot of percentage increase in expected optimal profit for all two-member coalitions \( \{i, j\} \) versus correlation \( \rho_{ij} \) for each hour of the day. Results are presented for three different price penalty ratios \( \gamma \in \{0.25, 0.50, 0.75\} \).

Contribution of decorrelation appears to be a decreasing function (on average) of the price penalty ratio \( \gamma \). The lack of monotonicity of profit increase with respect to correlation may be attributable to nonlinear dependencies not captured by the correlation coefficient.

Fig. 6 presents a graphical illustration of a core allocation \( x^* \in C \) to individual members of the grand coalition. Each member’s payoff \( x_i^* \) is shown as a bar decomposed into its baseline expected optimal profit \( v(\{i\}) \) and the incremental payoff \( x_i^* - v(\{i\}) \) derived from participating in the grand coalition. While the absolute expected payoff \( x_i^* \) to each coalition member tends to increase with \( \gamma \), the incremental payoff \( x_i^* - v(\{i\}) \) to each member appears to be insensitive to variations in \( \gamma \). This suggests that the reduction in CVaR deviation (19) resulting from aggregation is insensitive to \( \gamma \). From Fig. 7, we see that the incremental payments appear insensitive to variations in \( \gamma \) around 0.4. Further, the incremental payments must go to zero at the boundary points \( \gamma \in \{0, 1\} \), because \( \lim_{\gamma \uparrow 1} \Delta_N = \lim_{\gamma \downarrow 0} \Delta_N = 0 \).

From Figs. 3 and 7, we observe a strong dependency of the size of incremental payment a coalition member receives on the degree of correlation with other members in the coalition. For example, define the cumulative correlation that farm \( i \) has with all other members in the grand coalition as

\[
\hat{\rho}_i := \sum_{j=1}^{N} \hat{\rho}_{ij}. \tag{34}
\]

It is clear from Fig. 3 (left) that wind farm 2 exhibits the smallest cumulative correlation during hour 5. Wind farm 2 also receives the largest incremental payment for all \( \gamma \in (0, 1) \) according to Fig. 7. Further inspection reveals that an ordering of wind farms according to the magnitude of incremental payment received is roughly preserved by cumulative correlation in the sense that \( \hat{\rho}_i \leq \hat{\rho}_j \) implies that \( x_i - v(\{i\}) \geq x_j - v(\{j\}) \). Similar payment characteristics are observed for hour 18 as well. One might further infer from Figs. 3 and 7 that the magnitude of incremental payment a coalition member receives depends monotonically on its degree of cumulative correlation relative to that of other members.

**Remark 29 (Approximately Fair Allocations):** The previous intuition that increased decorrelation between members’ outputs leads to larger reductions in dispersion of the aggregate output may prove valuable in helping construct imputations \( \tilde{x} \in \mathbb{R}^N_+ \) that make transparent the impact of statistical correlation between different members’ outputs on the subsequent payment that each coalition member is entitled to—clarity that the linear programming solution technique (28) lacks. A subject of future research will be to develop approximately fair imputations \( \tilde{x} \) with clear interpretability in terms of the relationship between correlation structure and profit allocation, but with provable bounds on the distance from core. In other words, \( d(\tilde{x}, C) = \inf_{x \in C} |x - \tilde{x}| \leq \varepsilon \) for some \( \varepsilon \geq 0 \).
VI. CONCLUSION

Using coalitional game theory as a vehicle for our analysis, we have analyzed the benefits of aggregation attainable through the formation of a willing coalition among WPPs to pool their variable power to jointly offer the aggregate output as a single entity into a forward energy market. Having assumed transferable payoff and a value function defined as the maximum expected profit attainable through competitive contract offering, we have shown that the associated coalitional game is balanced. Consequently, the core of such a game is necessarily nonempty—or more simply, there exists a stabilizing profit sharing rule that is satisfactory from the perspective of every coalition participant. To this end, we propose a sharing rule—that minimizes worst-case excess for each coalition in the game—to fairly allocate the expected profit among coalition members.

Our results demonstrate that wind power aggregation and coalitional contract offering can serve as an effective means for improving wind power profitability in the face of future production uncertainty. However, our results are limited to the setting in which all WPPs are connected to a common single bus in the network. As the transmission network can severely constrain a coalition’s ability to directly aggregate wind power generated at different buses, we are presently working on extensions of these results to the multi-bus network setting to account for transmission effects.

APPENDIX

A. Proof of Lemma 4

Throughout the proof, we restrict ourselves to the set of expected imbalance prices such that \( \mu_q \geq p \). The results are similarly proven for the complementary case of \( \mu_q < p \).

Part 1) (Positive Homogeneity): Fix \( \alpha > 0 \). For brevity, let the stochastic process \( x \) inherit the properties and distributional notation associated with the wind process defined in Section II-A. Let \( \Gamma_\alpha(x; t) \) denote the marginal CDF associated with the positively scaled stochastic process \( \alpha x \). First observe that

\[
\Gamma_\alpha(x; t) = P\{\alpha x(t) \leq x\} = \Phi\left(\frac{x}{\alpha}; t\right).
\]

It follows that the time-averaged distribution \( G_\alpha(x) \) associated with the scaled process \( \alpha x \) is similarly given by

\[
G_\alpha(x) = \frac{1}{T} \int_0^T \Phi\left(\frac{x}{\alpha}; t\right) dt = F\left(\frac{x}{\alpha}\right).
\]

Using the previous identity \( G_\alpha(x) = F(x/\alpha) \), it follows that the \( \beta \) quantile of \( G_\alpha \) is given by

\[
G_\alpha^{-1}(\beta) = \alpha F^{-1}(\beta).
\]

Using the previous identity with Theorem 1, the desired result of positive homogeneity follows immediately:

\[
\Psi[\alpha x] = \mu_q T \int_0^T G_\alpha^{-1}(z) dz - \mu_\lambda \int_0^T G_\alpha^{-1}(z) dz
\]

\[
= \alpha \left( \mu_q T \int_0^T F^{-1}(z) dz - \mu_\lambda \int_0^T F^{-1}(z) dz \right)
\]

\[
= \alpha \Psi[x].
\]

The result for \( \alpha = 0 \) is trivial, as \( \Psi[0] = 0 \).

Part 2) (Superadditivity): Consider two stochastic processes \( x \) and \( y \): \[
\Psi[x] + \Psi[y] = \max_{C_\alpha \geq 0} E \Pi(C_\alpha, x, q, \lambda) + \max_{C_\beta \geq 6} E \Pi(C_\beta, y, q, \lambda)
\]

\[
- E \Pi(C_\alpha^*, x, q, \lambda) + E \Pi(C_\beta^*, y, q, \lambda)
\]

where \( C_\alpha^* \) and \( C_\beta^* \) are the optimizers of their respective maximization problems. It follows from Theorem 5 that

\[
E \Pi(C_\alpha^*, x, q, \lambda) + E \Pi(C_\beta^*, y, q, \lambda) \leq E \Pi(C_{x+y}^*, x+y, q, \lambda).
\]

Using this inequality, we can bound the sum \( \Psi[x] + \Psi[y] \) to obtain the desired result. More specifically

\[
\Psi[x] + \Psi[y] \leq E \Pi(C_{x+y}^*, x+y, q, \lambda)
\]

\[
\leq \Psi[x] + \Psi[y]
\]

where \( C_{x+y}^* = \arg \max_{C_\alpha \geq 0} E \Pi(C, x + y, q, \lambda) \).

ACKNOWLEDGMENT

The authors would like to thank the reviewers for the constructive comments that helped in improving the quality of the paper.

REFERENCES


BAEYENS et al.: COALITIONAL AGGREGATION OF WIND POWER


Enrique Baeyens received the Industrial Engineering and Ph.D. degrees from the University of Valladolid, Valladolid, Spain, in 1989 and 1994, respectively. He joined the University of Valladolid in 1997 where he is currently a Professor at the Department of Systems Engineering. From 1999 to 2002, he served as Associate Dean for Research at the College of Engineering of the University of Valladolid. In 2007, he became Director of Research of CARTIF, a Spanish application-oriented research organization which develops technological innovations and novel systems solutions for industrial customers and especially for SMEs. He also has served as Director of the Instituto de las Tecnologías Avanzadas de la Producción since 2012. His research interests include optimal control theory, modeling and system identification, and its applications to industrial and power systems.

Eliyan Y. Bitar received the B.S. and Ph.D. degrees from the University of California, Berkeley, CA, USA, in 2006 and 2011, respectively. He is currently an Assistant Professor and the David D. Croll Sesquicentennial Faculty Fellow in the School of Electrical and Computer Engineering at Cornell University, Ithaca, NY, USA. Prior to joining Cornell in the Fall of 2012, he was engaged as a Postdoctoral Fellow in the Department of Computing and Mathematical Science (CMS) at the California Institute of Technology and at the University of California, Berkeley, in Electrical Engineering and Computer Science during the 2011–2012 academic year. His research interests include stochastic control and game theory and their applications to power systems.

Pramod P. Khargonekar received the B.Tech. degree in electrical engineering from the Indian Institute of Technology, Bombay, India, in 1977, the M.S. degree in mathematics, and the Ph.D. degree in electrical engineering from the University of Florida, Gainesville, FL, USA, in 1980 and 1981, respectively. After holding faculty positions in Electrical Engineering at the University of Florida and University of Minnesota, he joined The University of Michigan in 1989 as Professor of Electrical Engineering and Computer Science. He became Chairman of the Department of Electrical Engineering and Computer Science in 1997 and also held the position of Claude E. Shannon Professor of Engineering Science. In July 2001, he rejoined the University of Florida and served as Dean of the College of Engineering until July 2009. He is currently Eckis Professor Electrical and Computer Engineering at the University of Florida.

Kameshwar Poolla received the B.Tech. degree from the Indian Institute of Technology, Bombay, India, in 1980, and the Ph.D. degree from the University of Florida, Gainesville, FL, USA, in 1984, both in electrical engineering. He served on the faculty of the University of Illinois, Urbana, IL, USA, from 1984 to 1991. Since then, he has been at the University of California, Berkeley, CA, USA, where he is the Cadence Distinguished Professor of Mechanical Engineering and Electrical Engineering & Computer Sciences. He also serves as the Founding Director of the IMPACT Center for Integrated Circuit manufacturing at the University of California. He co-founded OnWafer Technologies, which offers metrology-based yield enhancement solutions for the semiconductor industry. OnWafer was acquired by KLA-Tencor in 2007. His current research interests covers many aspects of the smart grid: renewable integration, demand response, cybersecurity, and sensor networks.

Dr. Poolla has been awarded a 1988 NSF Presidential Young Investigator Award, the 1993 Hugo Schuck Best Paper Prize, the 1994 Donald P. Eckman Award, the 1998 Distinguished Teaching Award of the University of California, the 2005 and 2007 IEEE Transactions on Semiconductor Manufacturing Best Paper Prizes, and the 2009 IEEE CSS Transition to Practice Award.