From *Systematic* Risk to *Systemic* Risk: Analysis Over Day-Ahead Market Operation Under High Renewable Penetration by CoVaR and Marginal CoVaR

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Abstract—**Traditional power market risk studies focus on *systematic* risk analysis which relies on value-at-risk (VaR) or conditional value-at-risk (CVaR) to measure potential financial losses resulting from renewable generation uncertainties. However, systematic risk only reflects the risk of a single entity and cannot capture the *systemic* risk which measures the risk contribution from a market participant to the overall market or the risk connection between two different market participants. With the rapid integration of renewable energy resources, it is essentially important to identify which renewable assets contribute a higher risk to market operations. Therefore, we propose two *systemic* risk measures, Contagious VaR (CoVaR) and marginal CoVaR (ΔCoVaR), to construct the risk connection network of the energy market under high renewable penetrations. Then, based on ΔCoVaR, a new index called normalized ΔCoVaR is built for market operators to evaluate the per MW impact on ΔCoVaR. Further, this paper proposes two approaches to manage the *systemic* risk in a day-ahead (DA) market, depending on regulation purposes. Finally, the proposed risk measures and management methods are applied to analyze a DA market with over 30% renewable energy penetration in a modified IEEE 118-bus system.**

Index Terms—**Systematic risk, systemic risk, risk analysis, contagious value-at-risk (CoVaR), high-penetration renewable generation, electricity market.**

NOMENCLATURE

Sets and Indicis

$C(Ri)$	Event set for renewables i
N_w, N_s	Set of wind farms and solar farms
N_g, N_d	Set of generators and loads
N_a	Set of units for ancillary services
$N^{samples}$	Set of samples within a sampling step
N^{total}	Set of total samples
L	Set of transmission lines
w, so	Indicis for wind farm and solar farm

Parameters

$a_i, a_i{}^w, a_i{}^{so}$	Bidding prices for traditional generators, wind farms, and solar farms
A^w	Wind rotor swept area
A^{so}	Irradiation area for a solar farm
b_i	AGC bidding price for unit i
c_i	Reserve bidding price of unit i
Cp	Wind rotor efficiency
D_i	Total AGC requirement
D_R	Total reserve requirement
E_{ph}	Photon energy
$F_{\max}, F_{\min}$	Up and down transmission capacity
GSF_{l-i}	Generation shift factor matrix
H, H_{ref}	Altitude for wind farm location and reference point
I_{sa}	Diode saturation current
K	Boltzmann's constant
Pr_s	Probability of scenarios
$P_{\max}, P_{\min}$	Up and down generation capacity for traditional generator i
Pen	Penalty for excessive renewable generations
P_{rated}	Maximum wind power
$P_i{}^l$	Load at bus i
R^u, R^d	Up and down regulation speed for AGC
Rs	Solar cell series resistance
$Step$	Step size for PDF sampling
T	Temperature
$W_{irradiance}$	Solar irradiance
$\pi_{i,s}^{RT}$	RT market price for bus i at scenarios
ρ	Air density
V	Wind speed
q	Electron energy
n	Ideality factor

Variables

$A_i{}^+, A_i{}^-$	Up and down regulating reserve of unit i
$CoVaR_q^{i\|B}$	CoVaR for renewables i at confidence level q
$es_i{}^w, es_i{}^{so}$	Generation shortage of wind farms and solar farms
eo^w, eo^{so}	Curtailed excessive generation of wind farms and solar farms
EK	Total generation deviation from the DA schedule

p_i, p_i^w, p_i^{so}	Scheduled generation of traditional generators, wind farms, and solar farms
R_i	Dispatched reserve of unit i
SC^s	Cost at scenario s
SC^{avg}	Market average cost
VaR_i^q	VaR for renewables i at confidence level q
X^i, X^{sys}	Potential monetary loss for renewables i and market
Y_i	Regression sample i
β_i	AGC participation factor of unit i
π_s^{DA}	DA market price for bus i at scenarios
$\tau_{l,u}^s, \tau_{l,d}^s$	Lagrangian multipliers for transmission capacity constraints
λ	Lagrangian multiplier for power balance constraint
$\Delta CoVaR_q^{i\|B}$	ΔCoVaR for renewables i at confidence level q

I. INTRODUCTION

TOWARDS a more environmentally sustainable grid design, the increasing deployment of renewable generation significantly alters traditional energy system operations. Many countries have been gradually eliminating fossil fuel usage and shifting to renewable energies. Denmark and Ireland have produced over 30% of net electricity loads by renewable energy sources [1]. China has installed 728 GW total capacity of renewable generation and has planned to achieve more than 15% renewable penetration by 2020 [1]. The U.S. also seeks to boost renewable integration and anticipates a power grid with 80% renewable penetration by 2050 [2].

As green technologies and renewable energy integrations continue to grow, so do the concerns regarding the impact of uncertainty due to the non-dispatchable nature of renewable generation. Especially under the current two-settlement market scheme, the day-ahead (DA) market endures greater pressure because forecast errors lead to dispatches of fast start-up units or real-time (RT) regulation services, which diminish social welfare. Thus, quantifying and regulating the risk brought by high renewable penetration poses a huge challenge to economical and efficient energy market operations.

The literature has suggested some research directions that are related to risk management in a power market operation. In [3], the CVaR is applied to provide a risk-averse bidding strategy for electric vehicle aggregators in DA market operations. A risk-averse bidding strategy based on CVaR for the microgrid is provided in [4]. In [5], a CVaR-based risk evaluation is combined with stochastic programming to provide a bidding strategy for the microgrid aggregators and virtual power plants. In [6], a robust optimization model combined with CVaR is proposed to construct a bidding strategy for wind farms and energy storage. Similarly, Ref. [7] provides a CVaR constrained robust optimal bidding model for controllable loads in DA and RT markets. Ref. [8] proposes a risk-averse optimal offering model for a virtual power plant trading in a joint market of energy and spinning reserve services. Ref. [9] delivers a scenario-based CVaR model for gas units participating in energy and regulation markets. In [10], CVaR is applied to forge a risk-averse joint offer for a group of wind producers in DA market operations. The above research

works have explored risk-averse bidding strategies of different power market participants aiming to regulate the risk of profit variability to a bearable amount.

Meanwhile, an effective risk assessment method is crucial to a reliable and efficient energy trading platform from the ISO's perspective. To provide a risk-averse market-clearing solution, Ref. [11] proposes a risk mitigation economic dispatch based on the optimal operation of wind farms and FACTS devices. In [12], a cooperative risk-averse trading mechanism is proposed for community-level system operation where energy-hubs and solar producers locate. In [13], CVaR is applied to model financial losses due to forecast errors, and a risk-cognizant dispatch is modeled. In [14], a multi-objective market-clearing model is proposed considering potential load-reduction risk in the DA market. Ref. [15] provides a risk-aware unit commitment model based on the line transfer margin. In [16], a trading mode for the multi-energy microgrid is proposed where CVaR models the risk from energy supply and demand. All these works deal with market operation considering risk from the ISO's perspective.

However, previous risk management works in the energy market focus either on the profitability of market participants or the risk-averse solution for a reliable energy trading mechanism. In the theory of risk management in finance, systematic risk is referred to as the risk carried in a system as a whole or any individual within a system, while systemic risk represents the risk of an entity affecting the overall system or operation, namely the ripple effect [17]. Prevailing risk indices in power market analysis, such as VaR and CVaR, are systematic risk measures that do not reflect the risk connections between the power market and market participants [18]. Few articles discuss systemic risk as it relates to the broad energy sector. Ref. [19] proposes a marginal risk index (EnsysRisk) to measure the total cost of energy impact on other economic commodities (e.g., coal and natural gas) during an energy crisis. Similarly, in [20], the systemic risk in a trading network between coal, oil, gas, and electricity is analyzed. However, those works emphasize the risk connection between the electricity market and other financial markets, and there is no work discussing the systemic risk among different players in a power market.

Therefore, previous works have not investigated the *systemic* risk within a power market under high renewable penetration, including how renewable aggregators interfere each other in the sense of risk connection, and how much risk a particular renewable aggregator contributes to the overall market operation. To the best of our knowledge, no study has conducted a *systemic* risk analysis of power market operations, and this is the first attempt to understand the systemic risk between renewables participants and DA market operations.

In this paper, *systemic* risk indices are proposed to analyze the risk interaction within a DA market, and two possible risk management methods are developed. The main contributions of this paper are three-fold:

1) We first propose a measure of *systemic* risk in the energy market, CoVaR, assessing the risk of the market at the time a particular event occurs to a renewable resource. Further, a marginal CoVaR (ΔCoVaR) index is proposed to measure risk sensitivity.

2) Based on the ΔCoVaR, a normalized ΔCoVaR index, is proposed to identify low-quality renewables. Two methods are proposed to regulate *systemic* risks due to renewable generation intermittency.

3) The proposed risk indices and risk management methods are applied to analyze a DA market with over 30% renewable energy penetration in the IEEE 118-bus system where the relationship between the risk of renewable assets and the risk of the overall market is tightly coupled.

The rest of this paper is organized as follows. Section II first presents the DA market model with renewable energy penetration and then gives a detailed comparison between systematic risk and *systemic* risk in energy markets. Next, the construction of a *systemic* risk index and regulatory methods are discussed. In Section III, real historical weather data from eight areas are collected and analyzed to formulate the cumulative probability distribution and the probability density function. Then renewable generation models are presented. Section IV presents the simulation results for the proposed risk index and risk management methods on the IEEE 118-bus system. Finally, a conclusion is drawn in Section V.

II. PROPOSED RISK ANALYSIS ON CURRENT MARKET OPERATION

A. Systematic Risk vs. Systemic Risk on DA Market Operation With High Renewable Penetration

1) Market Clearing Model: A two-settlement market scheme is widely adopted in U.S power market operations [34]. A typical DA market clears base generations and a RT market offers adjustments to the deviation in DA dispatches [21]. With increasing renewable integration, the mismatch between the DA dispatch results and RT dispatch results is exaggerated. Reserves are cleared along with generation dispatches including automatic generation control (AGC) reserves and spinning reserves. Reserves cleared in the DA market are the capacity, and RT regulation generation depends on the actual deviation [22].

The joint energy and ancillary service dispatch considering renewable penetration is formulated as a two-stage stochastic model shown in (1)–(15) [23].

$$\min \sum_i^{Ng} a_i p_i + \sum_i^{Nw} a^w_i p^w_i + \sum_i^{Ns} a^{so}_i p^{so}_i$$
$$+ \sum_i^{Na} b_i(A^+_i + A^-_i) + \sum_i^{Ng} c_i R_i + \text{EC} \qquad (1)$$

$$EC = \sum_s^{Ns} pr_s \left[\pi_s^{RT} \left(\sum_i^{Nw} es^w_{i,s} + \sum_i^{Nso} es^{so}_{i,s} \right) \right.$$
$$\left. + pen \left(\sum_i^{Nw} eo^w_{i,s} + \sum_i^{Nso} eo^{so}_{i,s} \right) \right] \qquad (2)$$

$$\sum_i^{Nd} p^l_i - \sum_i^{Nw} p^w_i - \sum_i^{Ns} p^s_i = \sum_i^{Ng} p_i \qquad (3)$$

$$\sum_i^{Ng} R_i \geq D_R \qquad (4)$$

$$\sum_i^{Na} A^+_{i,s} \geq D_i \forall s \in Ns \qquad (5)$$

$$\sum_i^{Na} A^-_{i,s} \geq D_i \forall s \in Ns \qquad (6)$$

$$R^u_{i,s} \geq A^+_{i,s} \geq 0 \quad \forall i \in Ng, \; \forall s \in Ns \qquad (7)$$

$$R^d_{i,s} \geq A^-_{i,s} \geq 0 \quad \forall i \in Ng, \; \forall s \in Ns \qquad (8)$$

$$P_i^{\max} \geq p_i + R_i \geq P_i^{\min} \quad \forall i \in Ng \qquad (9)$$

$$p_i + R_i - A^-_{i,s} \geq P_i^{\min} \quad \forall i \in Ng \; \forall s \in Ns \qquad (10)$$

$$P_i^{\max} \geq p_i + R_i + A^+_{i,s} \quad \forall i \in Ng \; \forall s \in Ns \qquad (11)$$

$$EK^s = \sum_i^{Nw} es^w_{i,s} + \sum_i^{Nw} es^s_{i,s} - \sum_i^{Nw} eo^w_{i,s}$$
$$- \sum_i^{Nw} eo^s_{i,s} \forall s \in Ns \qquad (12)$$

$$F^{\max}_l \geq \sum_i^{Ng} GSF_{l-i}(p_i + \beta_{i,s} EK^s)$$
$$+ \sum_i^{Nw} GSF_{l-i}(p^w_i - es^w_{i,s} + eo^w_{i,s})$$
$$+ \sum_i^{Nso} GSF_{l-i}(p^s_i - es^s_{i,s} + eo^s_{i,s})$$
$$- \sum_i^{Nl} GSF_{l-i} p^l_i \geq F^{\min}_l, \forall s \in Ns \qquad (13)$$

$$\sum_i^{Ng} \beta_{i,s} = 1 \forall s \in Ns \qquad (14)$$

$$A^+_{i,s} \geq \beta_i EK \geq -A^-_{i,s} \quad \forall i \in Ng, \forall s \in Ns \qquad (15)$$

The objective function represents the minimization of the total cost and *EC* represents possible losses induced by uncertainties. Therefore, in this formulation, the risk includes monetary losses and opportunity cost: *(1)* we expect the renewable generation deviation to be compensated in RT operation. Expensive fast-start-up units or regulation units may be dispatched to balance the mismatch which could have been supported by cheap base units; *(2)* Unexpected excess renewable generations are wasted due to security considerations. The market would have cleared the excess renewable generations because renewable generations are usually cheaper than traditional units. The DA power balance is modeled in (3), which shows the demand is satisfied by both renewable and traditional units. The total reserve requirement is defined in (4), and Eqs. (5)–(6) ensure sufficient AGC up and down capacity in the system. Constraints (7)–(11) describe the
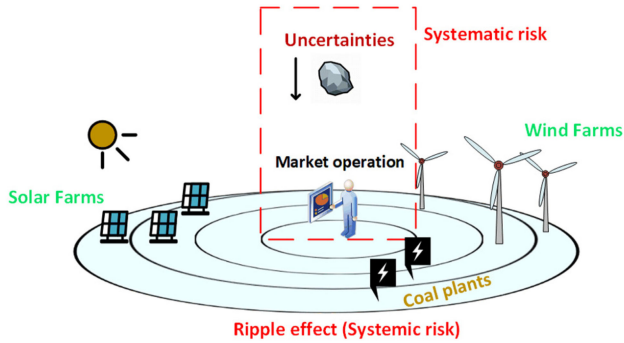
Fig. 1.   Systemic risk and systematic risk in energy market.

relationship between generation and reserves. Constraint (12) represents the deviation of renewable generations from forests. Constraint (13) is the line flow limit, and (15) ensures that the reserve can compensate for the shortage from renewable generation uncertainty.

2) Systematic Risk VS. Systemic Risk: Systematic risk and systemic risk are two similar terms but have entirely different definitions in finance. The common "market risk" referred to in energy market studies is systematic risk, which describes how vulnerable a market or a particular bidder is under extreme events. The systemic risk we analyze in this paper refers to the *interlinkages* and *interdependencies* among entities within a market operation. Systemic risk represents the risk of the crash of a system or market associated with the risk in an individual entity, group, or component in a system [17].

In the energy market context, systematic risk due to the intermittent characteristics of renewable energy has been studied thoroughly. VaR and CVaR are prevailing systematic risk indices evaluating the risk of a market participant like a renewable generation owner or the whole market like a DA market in isolation. However, the risk of a renewable generator owner does not necessarily reflect its contribution to the financial risk of the whole market or its connection to another renewable generator. The relationship between systematic risk and systemic risk is shown in Fig. 1.

The market operation under normal operation is a still lake if the forecast is 100% accurate. The intermittent characteristic of renewable resources is similar to throwing a stone to the lake. Then, the traditional systematic risk evaluates the momentum of the stone (size, weight, etc.), while the proposed systemic indices capture the ripple effect affecting other entities. Therefore, management of the systematic risk ensures that the potential loss under some uncertainty is bearable from the perspective of the entire system. In contrast, regulation of the systemic risk provides a structurally stable renewable energy source (RES) portfolio, which tends to avoid the case that a single RES unit's uncertainty has too much impact (e.g., higher than the CoVaR threshold) on the market-clearing risk leading to a large social welfare loss, such as an economic cascading failure.

Thus, the proposed systemic index aims to deliver an evaluation of such interlinks, which provides a measure of how tightly different entities are linked together. That is, the more coupling

among all players, the higher the risk of a total system failure we may have; the less coupling among all players, the lower the risk of a total system failure. The new *systemic* risk indices discussed in this paper provide such "coupling" information, which can be used for further potential mitigation of the possible economic failure. In contrast, the traditional *systematic* risk assessment does not provide such information.

B. Systemic Risk Index Construction

In this section, we analyze the systemic risk between the overall market operation and renewable energy resource bidders by constructing the systemic risk index, CoVaR, and ΔCoVaR. The CoVaR index is a recently proposed measure for evaluating banking system risk [18], [28]. Here, we redefine and reformulate CoVaR and ΔCoVaR to analyze the systemic risk in the context of the energy market with uncertainties. The reformulated indices have the same properties with the original indices in [18] and [28].

Although the operator has the lowest expected cost under market solutions from (1)–(15), the potential loss could be high in extreme cases. The cost for the DA market under a specific dispatch in a scenario *s* is shown in (16).

$$
\begin{aligned}
SC^s = & \sum_i^{Ng} a_i p_i + \sum_i^{Nw} a^w_i p^w_i + \sum_i^{Ns} a^{so}_i p^{so}_i + \sum_i^{Na} b_i (A_i^+ + A_i^-) \\
& + \sum_i^{Ng} c_i R_i + \pi_s^{RT} \left(\sum_i^{Nw} es^w_{i,s} + \sum_i^{Nso} es^{so}_{i,s} \right) \\
& + pen \left(\sum_i^{Nw} eo^w_{i,s} + \sum_i^{Nso} eo^{so}_{i,s} \right)
\end{aligned}
\tag{16}
$$

The participation of renewable generation owners in the electricity market is no longer negligible considering their rapidly increasing capacity. Renewables' financial incentives need to be driven by a locational marginal price (LMP) instead of a fixed rate. The LMP is formulated from the dual variables of (3)–(15). For a renewable generation owner who has multiple solar and wind farms, the monetary gain is described in (17).

$$
R = \pi_s^{DA} \left(\sum_i^{Nw} p^w_i + \sum_i^{Nso} p^{so}_i \right) - \sum_i^{Nw} a^w_i p^w_i - \sum_i^{Nso} a^{so}_i p^{so}_i
\tag{17}
$$

π_s^{DA} is the DA LMP representing the cost induced by an incremental load at a bus, which is the combination of Lagrangian multipliers associated with constraints (3) and (13). The Lagrangian function of (1)-(15) is formed in (18). Note that other constraints affect the value of λ, $\tau_{l,u}^s$ and $\tau_{l,d}^s$ to impact the LMP. For simplicity, only the constraints containing p_i^l term are included.

Therefore, π_s^{DA} is formed in (19). Different from a traditional deterministic formulation, uncertainty causes the Lagrangian multipliers in each scenario to take on a different value.

One of the challenges of current renewable integration is the DA forecast. A renewable owner suffers from buying the
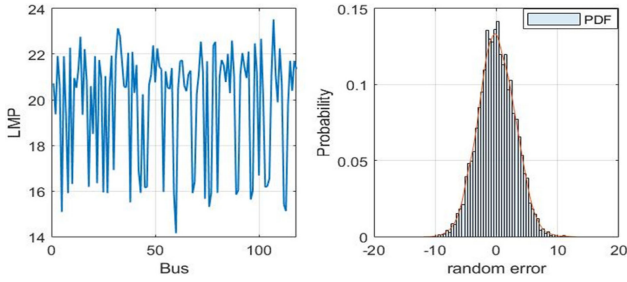
Fig. 2.   Real-time LMPs.

shortage from the RT market as shown in (20).

$$
\begin{aligned}
L = Obj + \lambda \left(\sum_i^{Nd} p^l_{\ i} - \sum_i^{Nw} p^w_{\ i} - \sum_i^{Ns} p^s_{\ i} - \sum_i^{Ng} p_i \right) \\
+ \sum_s^{Ns} \sum_{l=1}^{L} \tau^s_{l,u} \left(\sum_i^{Ng} GSF_{l-i}(p_i + \beta_{i,s} EK^s) \right) \\
+ \sum_i^{Nw} GSF_{l-i}(p^w_i - es^w_{\ i,s} + eo^w_{\ i,s}) \\
+ \sum_i^{Nso} GSF_{l-i}(p^s_i - es^s_{\ i,s} + eo^s_{\ i,s}) \\
- \sum_i^{Nl} GSF_{l-i} p^l_i - F^{max}_l \Bigg) \\
- \sum_s^{Ns} \sum_{l=1}^{L} \tau^s_{l,d} \left(\sum_i^{Ng} GSF_{l-i}(p_i + \beta_{i,s} EK^s) \right) \\
+ \sum_i^{Nw} GSF_{l-i}(p^w_i - es^w_{\ i,s} + eo^w_{\ i,s}) \\
+ \sum_i^{Nso} GSF_{l-i}(p^s_i - es^s_{\ i,s} + eo^s_{\ i,s}) \\
- \sum_i^{Nl} GSF_{l-i} p^l_i - F^{min}_l \Bigg)
\end{aligned}
\tag{18}
$$

$$
\pi_s{}^{DA} = \frac{\partial L}{\partial p^l_i} = \lambda - \sum_s^{Ns} \sum_{l=1}^{L} GSF_{k-l}(\tau^s_{l,u} - \tau^s_{l,d}) \forall k \in N_b
\tag{19}
$$

$$
C = \pi_s^{RT} \left(\sum_i^{Nw} es^w_{\ i,s} + \sum_i^{Nso} es^{so}_{\ i,s} \right)
\tag{20}
$$

Even in the DA time frame, RT price forecasting is a complex issue. Thus, we model the π_s^{RT} as a random variable based on historical data from PJM [24]. As shown in the left part of Fig. 2, we randomly select 118 buses from the PJM LMP database at the same time interval. The right part shows the forecast error following a normal distribution $N \sim (0, 9)$.

Therefore, the overall profit for a renewable bidder in the market operations is shown in (21).

$$
\begin{aligned}
P = \pi_s^{DA} \left(\sum_i^{Nw} p^w_{\ i} + \sum_i^{Nso} p^{so}_{\ i} \right) - \sum_i^{Nw} a^w_{\ i} p^w_{\ i} \\
- \sum_i^{Nso} a^{so}_{\ i} p^{so}_{\ i} - \pi_s^{RT} \left(\sum_i^{Nw} es^w_{\ i,s} + \sum_i^{Nso} es^{so}_{\ i,s} \right)
\end{aligned}
\tag{21}
$$

The proposed systemic risk is to formulate the connection of systematic risks in different entities. VaR is defined by the maximum loss in a portfolio under a certain confidence level q as shown in (22) [6]. Equations (23) and (24) show the formulation of VaR for the DA market and a renewable bidder.

$$
\Pr(X^i \leq VaR_i{}^q) = q
\tag{22}
$$

$$
VaR^{sys} = \min\{SC | F^{-1}(SC) \geq q : q \in [0,1]\}
\tag{23}
$$

$$
VaR^i = \min\{P | F^{-1}(P) \geq q : q \in [0,1]\}
\tag{24}
$$

Similarly, CVaR is defined as the expected value of loss exceeding VaR, as shown in equations (25) and (26) where z is the loss value, and F_X is the cumulative probability function. Then CVaR for the market and renewables are obtained as shown in (27) and (28).

$$
CVaR_a(x) = \int_{-\infty}^{+\infty} z dF^a_X(z)
\tag{25}
$$

$$
F^a_X = \left\{ \begin{array}{c} 0 z < VaR_a(x) \\ \frac{F_X(z)-a}{1-a} z \geq VaR_a(x) \end{array} \right\}
\tag{26}
$$

$$
CVaR_a(x) = \int_{-\infty}^{+\infty} SC dF^a_X(SC)
\tag{27}
$$

$$
CVaR_a(x) = \int_{-\infty}^{+\infty} P dF^a_X(P).
\tag{28}
$$

Then we define the energy market CoVaR as the risk (VaR or CVaR) existing in DA market conditioning on events $C(R^i)$ that occurred at a renewable, denoting $CoVaR_q{}^{sys|C(R)}$. In other words, $CoVaR_q{}^{sys|C(R)}$ is a q-quantile or expected shortfall of a conditional probability distribution. Therefore, the relationship between the risk of the DA market and the risk of an individual renewable asset is described in (29).

$$
\Pr(SC \leq CoVaR_q{}^{sys|C(R^i)} | C(R^i)) = q.
\tag{29}
$$

In this paper, we focus on the event when a renewable is at its VaR value (distress) as shown in (30). The same procedures can also be done by using CVaR.

$$
C(R^i) \triangleq \{R^i = VaR_q^{R^i}\}
\tag{30}
$$

Further, Marginal CoVaR (i.e., ΔCoVaR) is proposed to denote the market's VaR change when a renewable is under distress compared with a renewable under the median state, which is formulated in (31). ΔCoVaR describes the risk contribution of

a renewable asset to market operation.

$$\Delta CoVaR_q{}^{SC|R^i} = CoVaR_q{}^{SC|R^i=VaR_q^{R^i}}$$
$$- CoVaR_q{}^{SC|R^i=Median^{R^i}}. \qquad (31)$$

Additionally, the index can also be used to study the risk impact of a renewable to another if we replace the SC with R^j, as in (32).

$$\Delta CoVaR_q{}^{R^j|R^i} = CoVaR_q{}^{R^j|R^i=VaR_q^{R^i}}$$
$$- CoVaR_q{}^{R^j|R^i=Median^{R^i}} \qquad (32)$$

Similarly, if we switch the position of SC and R^i, this index signals which renewable is most at risk when the market is under crisis, as shown in (33).

$$\Delta CoVaR_q{}^{R^i|SC} = CoVaR_q{}^{R^i|SC=VaR_q^{SC^i}}$$
$$- CoVaR_q{}^{R^i|SC=Median^{SC^i}}. \qquad (33)$$

There are many ways to obtain CoVaR and ΔCoVaR as long as the correlation between the VaR value of the market and the VaR value of a renewable can be formulated [28]. We have opted to use quantile regression for its robustness [29], [30].

Standard regression describes the average relationship between regressors and the resulting variables. Quantile regression is different in that it views the relationship from a quantile perspective. If Y is a random variable, the cumulative distribution function is defined as in (34).

$$F(y) = \Pr(Y \leq y) \qquad (34)$$

Then the q-quantile is described by (35).

$$Q(q) = \inf\{y : F(y) \leq q\} \qquad (35)$$

If enough samples are generated, $q\%$ samples are smaller than the value of q-quantile and 1- $q\%$ samples are larger than the value of q-quantile. Assuming a set of samples $\{Y_1, \ldots, Y_n\}$ are generated from $F(y)$, quantile regression obtains the value of ε as in (36).

$$\min \sum_{i\in\{i:y_i-\varepsilon\geq 0\}} q|y_i - \varepsilon| + \sum_{i\in\{i:y_i-\varepsilon\geq 0\}} (1-q)|y_i - \varepsilon| \qquad (36)$$

Therefore, q-quantile is obtained in (37).

$$Q(q) = \arg\min_{\varepsilon\in R} \left\{ \sum_{i\in\{i:y_i-\varepsilon\geq 0\}} q|y_i - \varepsilon| \right.$$
$$\left. + \sum_{i\in\{i:y_i-\varepsilon\geq 0\}} (1-q)|y_i - \varepsilon| \right\} \qquad (37)$$

We apply the quadratic quantile regression model as described in (38) instead of the linear regression model detailed in [28], [29]. The quadratic regression model has, at a minimum, the same accuracy as linear regression because if the relationship is linear then the regressor for the quadratic term is zero. Then the market CoVaR conditional on a renewable at its VaR value is

estimated by (39) and the corresponding ΔCoVaR is estimated as in (40).

$$\arg\min_{\alpha,\beta\in R} \left\{ \sum_{i\in\{i:y_i-\varepsilon\geq 0\}} q\left| SC_i - \alpha - \eta R^i - \beta(R^i)^2 \right| \right.$$
$$\left. + \sum_{i\in\{i:y_i-\varepsilon\geq 0\}} (1-q)\left| SC_i - \alpha - \eta R^i - \beta(R^i)^2 \right| \right\} \qquad (38)$$

$$CoVaR_q{}^{sys|R^i=VaR_q^{R^i}} = \alpha + \eta VaR_q^{R^i} + \beta(VaR_q^{R^i})^2 \quad (39)$$

$$\Delta CoVaR_q{}^{R^i|SC} = \eta(VaR_q^{R^i} - VaR_{median}^{R^i})$$
$$+ \beta(VaR_q^{R^i} - VaR_{median}^{R^i})^2 \qquad (40)$$

C. Systemic Risk Management

In this section, two risk management methods are proposed to regulate systemic risk in the DA market based on different regulatory purposes.

1) Roll Out Policy: When operators find that market risk is no longer bearable, the most direct coping method is to roll out partial capacity of the renewables that have high risk contributions to market operations. We define a percentile ΔCoVaR as in (41). Further, we propose a new index called Normalized ΔCoVaR, denoted by q^p, as the proportion of the percentile ΔCoVaR and the share of a renewable's capacity (42). The market operator sets the threshold to restrain the maximum risk position that is allowed.

$$\%\Delta CoVaR_q{}^{SC|R^i} = \frac{\Delta CoVaR_q{}^{SC|R^i}}{VaR_q{}^{SC}} \qquad (41)$$

$$q^p = \frac{\Delta CoVaR_q{}^{SC|R^i} \sum_i p^i}{VaR_q{}^{(SC-SC^{avg})} p^i} \leq threshold. \qquad (42)$$

By regulating low-quality renewables, the market risk is reduced as much as possible with the smallest capacity being cut because a low quality index means market risk is more sensitive to those renewables' capacities.

However, cutting capacity has its pros and cons: reduced renewable capacity also leads to increased generation costs (renewable usually has a low cost), but the system risk is also reduced accordingly.

2) Asset Decomposition: Asset decomposition is applied when market risk is manageable and only a few renewables contribute most of the risks. This situation is not fair to high-quality renewable assets because the results of market clearing largely depend on the few low-quality renewables' behaviors. A market is more stable and balanced when all renewables contributes similar risk.

By equally dividing a high-risk renewable resource into several small renewable resources, any single small renewable has a lower risk of connection with either the market or other renewables. This conclusion is drawn from the cloning property of the ΔCoVaR. If a large system can be decomposed to n small components, the ΔCoVaR of the large system is the same as the sum of n components' ΔCoVaR. Therefore, the risk contribution
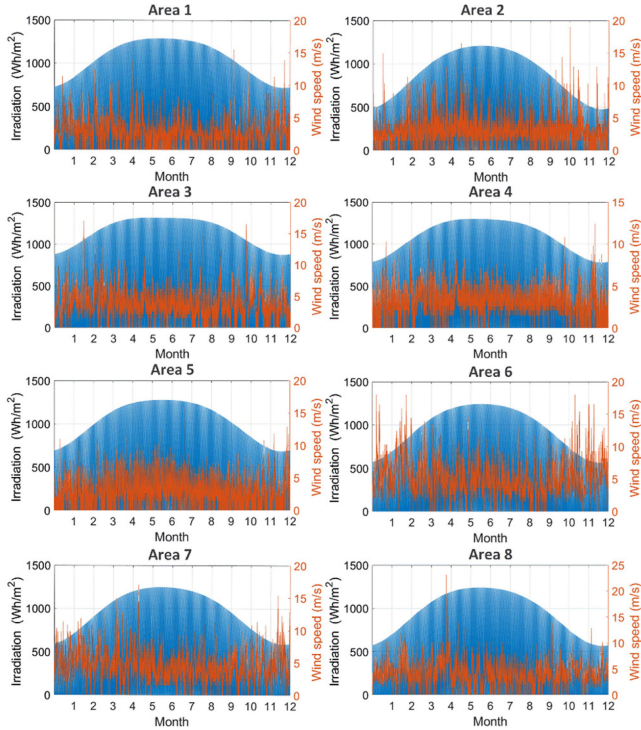
Fig. 3. Wind speed and solar irradiation.

Fig. 4. Wind speed and solar irradiance cumulative probability.

of a large renewable aggregator is the same as the sum of n smaller aggregators as shown in (43).

$$\Delta CoVaR_q^{sys|C(R^1,...,R^i)} = \sum_{i=1}^{n} \Delta CoVaR_q^{sys|C(R^i)} \quad (43)$$

Thus, from a planning perspective, multiple small capacity renewable assets are more welcome than a single large capacity renewable asset. For example, three 1 MW wind turbines are superior to one 3 MW wind turbine in the sense of a risk balanced market.

III. RENEWABLE GENERATION MODELING

Wind and solar energy are two of the most dominant renewable generation resources in the U.S. [25]. In this paper, we first collect typical meteorological year (TMY) data sets derived from the 1961–1990 and 1991–2005 National Solar Radiation Data Base archives for wind speed and solar irradiance in 8 different areas [26], [27]. Then, the collected yearly data are modeled to form cumulative probability functions and probability density functions.

A. Weather Data Collection and Analysis

Wind speed and solar irradiation substantially impact wind and solar generation. Weather forecasting is, therefore, paramount to accurate generation forecasting.

Fig. 3 shows the TMY data sets for wind speed and solar irradiation in eight different areas.

According to the historical data, we measure probability density using the samples located within a unit length as in
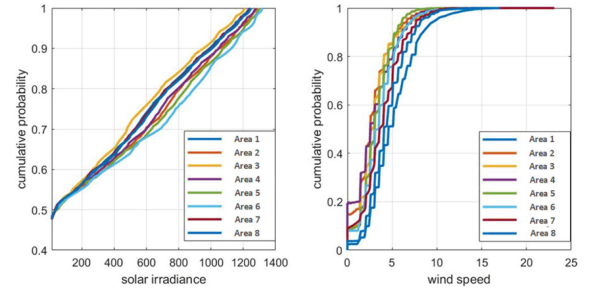
(44). Then the cumulative probability function is formulated by (45), as shown in Fig. 4. Interpolating the distribution by equally dividing a unit length provides a discretized probability distribution.

$$PDF = \frac{N^{samples}}{N^{total}step} \quad (44)$$

$$CDF = \sum_{Lowest}^{Current} PDF \quad (45)$$

The advantages of modeling the probability distribution through historical data over predefined functions such as Gamma distribution or Weibull distribution are that historical data reveal more intrinsic characteristics associated with different renewable owners. However, predefined functions model all renewables and have similar distributions.

B. Renewable Energy Generation

Available wind power can be formulated by a function of wind speed and wind turbine parameters, as shown in (46) [31].

$$P_{wind}(\omega) = \begin{cases} 0 & 0 \leq \omega \leq \omega_1 \\ kC_p 1/2\rho A^w V^3 & \omega_1 \leq \omega \leq \omega_r \\ P_{rated} & \omega_r \leq \omega \leq \omega_{cut-out} \\ 0 & \omega \geq \omega_{cut-out}. \end{cases} \quad (46)$$

The historical wind speed data in part *A* is measured at 10 meters in height. The wind speed is recalculated according to the altitude of different wind farms, as shown in (47). Excess wind generation is curtailed if the wind speed exceeds the limit $w_{cut-out}$.

$$V_{heigh} = V_{ref} \left(\frac{H}{H_{ref}} \right)^a \quad (47)$$

Solar cells are usually modeled by an ideal current source with a parallel diode. Photons from solar irradiation transmit energy to electrons in the P-N junction and then the energized electrons jump to the circuit generating current. The solar panel I-V curve is modeled by (48), and (49) gives solar power [32].

$$I = A^{so}q\frac{W_{irradiance}}{E_{ph}} - Isa\left[\exp^{(\frac{q(Vph+RsI)}{nKT})} - 1\right]$$

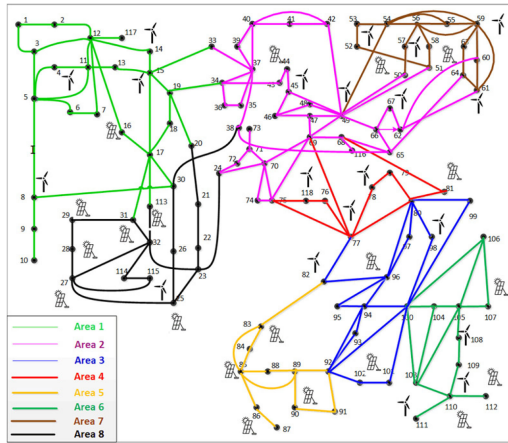$$- \frac{Vph + RsI}{Rsh} \quad (48)$$

Fig. 5.   IEEE 118-bus with high renewable penetrations in 8 areas.

$$P = \left\{ A^{so} q \frac{W_{irradiance}}{E_{ph}} - Isa \left[\exp^{\left(\frac{q(Vph+RsI)}{nKT} \right)} - 1 \right] \right.$$
$$\left. - \frac{Vph + RsI}{Rsh} \right\} V \qquad (49)$$

In summary, in Subsection III-A, realistic probability distributions for wind speed and solar irradiance in each area are calculated. Then, according to (46)–(49) in Subsection III-B, wind and solar power outputs in each scenario can be generated. Therefore, the market model related variables such as pr_s, $es_{i,s}^w$, and $es_{i,s}^{so}$ discussed in Section II can be properly modeled based on real historical data to facilitate the calculation of CoVaR and ΔCoVaR.

IV. CASE STUDY

In this section, a comprehensive systemic risk analysis is provided over the DA market operation in a modified IEEE 118-bus system. The proposed systemic risk indices describe the risk contribution of renewable generation participants to the risk of the whole market operation. In the same vein, the risk connections between each renewable asset are also investigated. The quality of each renewable asset is, therefore, determined. Then two risk management methods are applied to regulate renewables with high risk contributions.

In this study, the original IEEE 118-bus system is divided into 8 different areas A1- A8 to implement the renewable assets discussed in Section III. Fig. 5 shows the system diagram and renewable asset locations. Each area is also considered as one renewable bidder. Other system specifications are included in [33].

The case study is divided into the following 3 parts (subsections A, B and C) to illustrate the procedure of conducting a systemic risk analysis in the energy market and demonstrate the effectiveness of the proposed management methods.
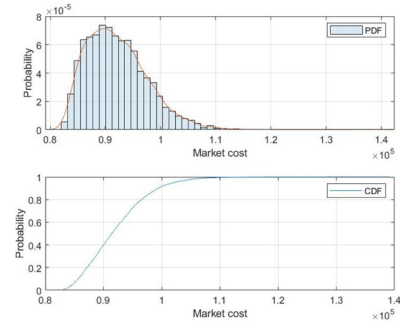

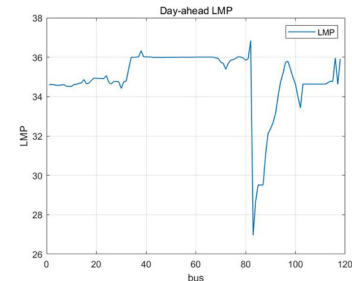Fig. 6.   DA market cost distribution.

Fig. 7.   DA LMPs.

A. Two-Stage Market-Clearing Results

DA market clearing is determined through the two-stage stochastic model formulated in (1)–(15), which provides a dispatch result with the lowest expected cost. Based on the historical data of wind and solar generation, numerous market settlements are obtained. Fig. 6 shows a fitted probability distribution of the market operation cost. The obtained DA LMP is shown in Fig. 7. Then the monetary gain for each renewable is obtained. The VaR of the DA market dispatch total cost is $98,285, and the VaR of the market cost deviates from its average by $6,334.

B. Conducting a Systemic Risk Analysis

The goal of the proposed systemic risk indices is to gauge the co-movement (i.e., the ripple effect) between the risk of different market participants and the risk of the whole market operation. The formulation of the proposed systemic risk indices relies on quantile regression, as discussed in the previous section. Here, 50,000 scenarios based on the historical data are generated to formulate the systemic risk indices, CoVaR, and ΔCoVaR, as shown in Fig. 8. From the regression curve, Area 2, Area 4, and Area 7 have less co-movement with market risks. It is worth noting that renewables with higher VaR can have lower CoVaR and ΔCoVaR values, such as, for example, Area 8 and Area 5, which have $4,259 and $2,873 in VaR but $612 and $650 in ΔCoVaR respectively. This observation is aligned with the previous conclusion that the risk of a renewable generator owner does not necessarily reflect its contribution to the financial risk of the whole market. Further, Area 5 has the highest ΔCoVaR value, which means it contributes to the risk of market operation
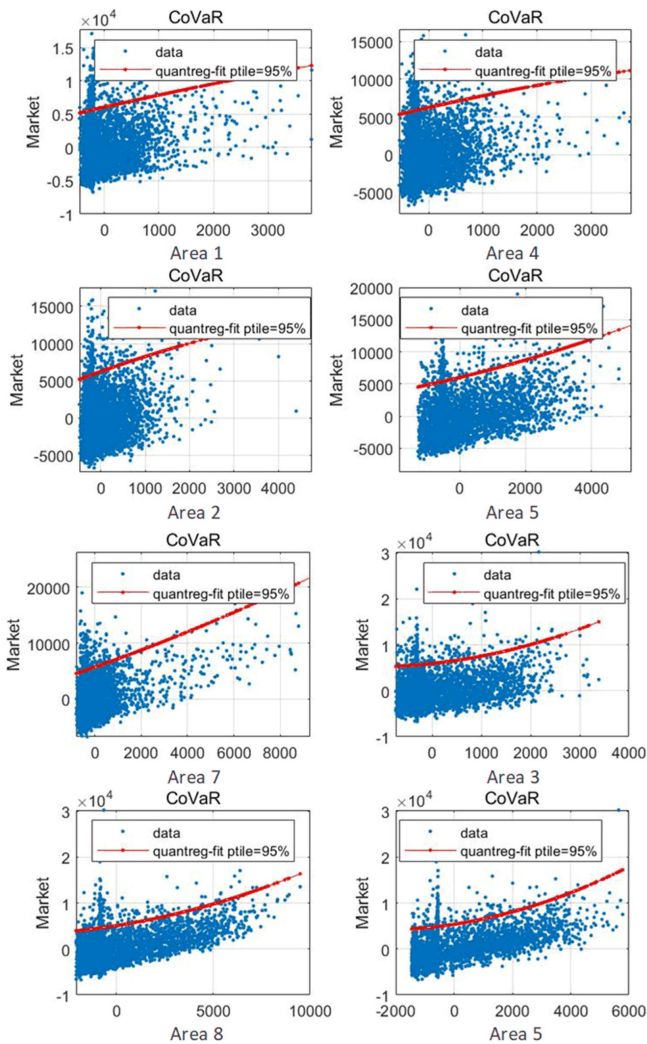
Fig. 8. Quantile regression of each renewable to DA market.

TABLE I
NORMALIZED ΔCoVaR of EACH RENEWABLE

Area 1	Area 2	Area 3	Area 4
0.81	0.84	0.51	0.71
Area 5	Area 6	Area 7	Area 8
0.89	0.70	0.72	0.36

more than the rest of the renewable owners. However, the larger the renewable capacity, the higher the risk contribution could be. Therefore, ΔCoVaR only represents the risk contributions but not the quality of the renewable asset. Then, the next step in this case study is to determine the quality of each renewable asset based on the proposed approach.

As shown in Table I, the Normalized ΔCoVaR is calculated for renewable plants at all areas. The quality of each renewable is ranked for further risk management. It is notable that although Area 8 has a higher ΔCoVaR and VaR than most renewables, it has a lower value of Normalized ΔCoVaR (i.e., lower impact or
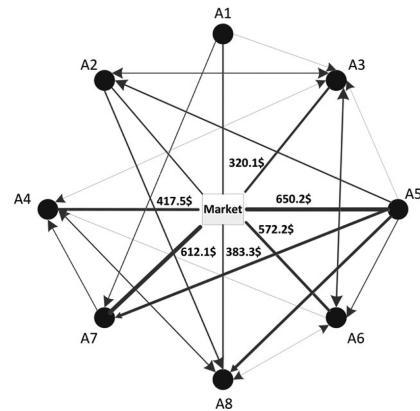

Fig. 9. Systemic risk network of renewables in DA market.

less risky per MW) than all other renewable resources because of its sizeable renewable capacity.

From the risk-based quality evaluation, Area 8 has the highest quality, and Area 5 has the worst quality, which may require regulation actions.

After the systemic risk indices for all entities are obtained, the risk network can be built. Intuitively, the risks of each renewable depend only on weather forecast accuracy and do not relate to each other. However, each renewable's bidding strategy and forecast affect the market price, which in turn affects other renewables' profit. It is known as the spillover effect, which indicates the impact of one event on another indirectly related event. By formulating the ΔCoVaR between each renewable as in (37), the spillover effect between each renewable is measured.

Therefore, the overall systemic risk network in the DA market constructed in Fig. 9 describes both the relationship between market risk and individual renewable risk and the relationship between each renewables' risk. The heavier the weight of the connecting line is, the stronger the risk impact is. By definition, the ΔCoVaR is directional, and thus we take the average to show the risk connection in Fig. 9.

In this subsection, we show the procedures of conducting a systemic risk analysis, and finally, the risk network for energy market operation is built. The operator can regulate the identified low-quality renewable assets, as shown in the next subsection.

C. Systemic Risk Management

From the systemic risk network and quality rank list, renewables in Area 5 contribute more risk to the market and are of low quality. Thus, market operators decide to intervene and regulate the systemic risk network to prevent potentially significant social welfare loss.

Depending on the purpose of the regulation, market operators can either perform the roll-out policy or asset decomposition. If market operators want to reduce potential monetary loss significantly, the roll-out policy is the most direct method. As shown in Fig. 10, the risk of the market is reduced after the risk management. However, a substantial reduction in capacity wastes low-cost renewable generations. Here, we select a compromised solution to reduce to 30% capacity in Area 5 as an
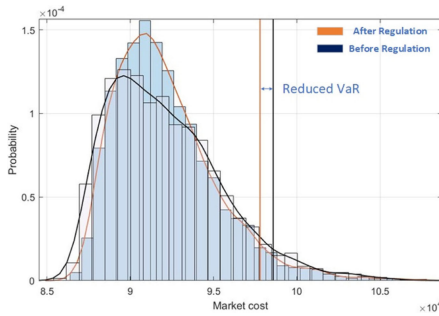
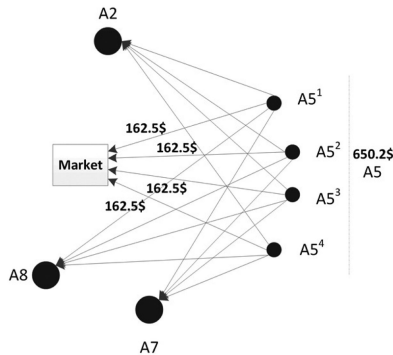Fig. 10.   Risk reduction of the DA market cost.

Fig. 11.   Risk connections of renewables at Area 5.

example. Potential future work could establish an optimization framework to determine the ideal reduction for low-quality renewable generations.

Another possible management approach is asset decomposition, which is applied when market operators find that an individual has an excessive risk impact on the market or other bidders, although the total market risk is bearable. From Fig. 9, the renewable owner in Area 5 has the strongest connecting edge to the market and affects risks of renewable owners at all Areas except Area 1. We decompose the renewable asset at Area 5 into four assets with equal capacity, as shown in Fig. 11. Then, the systemic risk for the total asset in Area 5 of $650.20 is decomposed to 4 smaller assets worth only $162.50 individually. Furthermore, the risk connections between Area 5 and Area 3, Area 4 and Area 6 become negligible. Therefore, following the regulation approach via asset decomposition, the risk network of the market operation is more balanced, and no individual can heavily influence market risk.

V. Conclusion

In this paper, the difference between traditional *systematic* risk analysis and the proposed *systemic* risk analysis in the electricity market is introduced. Then, two indices, CoVaR and ΔCoVaR, are proposed for systemic risk analysis in the energy market. Next, the systemic risk connection network in the DA market with high renewable penetrations is formulated based on the proposed indices. Furthermore, with the systemic risk indices, we construct a quality index, Normalized ΔCoVaR,

which provide ISOs with the quality (in terms of systemic risk) of each renewable generation asset. Finally, two risk management methods are provided, depending on the current market situation.

This paper delivers a complete procedure to conduct a systemic risk analysis in the energy market from formulations to regulations. Future work may lie in a joint management strategy of systematic risk and systemic risk in a power market operation, which provides a comprehensive risk-averse economic dispatch.

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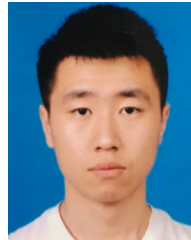
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