Financial Resilience and Financial Reliability for Systemic Risk Assessment of Electricity Markets with High-Penetration Renewables

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***Abstract*—Over the past 20 years, the rapid integration of renewable energy has resulted in electricity markets that are increasingly complex, interconnected, and uncertain. Similar to the banking system's financial crisis in 2008 due to chained reactions, severe financial losses due to uncertainty at a large renewable farm could induce significant financial losses at other market participants. The spread of such financial shocks can be worsened by centralized market clearing, and systemic financial risks consequently germinate in electricity market operations. Therefore, our previous work has compared *systemic* risk with *systematic* risk in the electricity market with uncertainties. However, the scope of our previous work has been limited to risk indices. This paper aims to broaden the study by proposing the theoretical foundation of systemic risk analysis in electricity markets with uncertainties. First, an electricity market financial network is defined to describe the cash inflow/outflow of all participants, and the financial contagion is employed to model the interlinks between two entities. Then, two financial properties, financial resilience and financial reliability, are proposed to evaluate the systemic risk in market settlements with uncertainties. Finally, the proposed theoretical foundation of systemic risk is demonstrated on the Texas synthetic 2000-bus system with 70% renewable penetration.**

***Index Term*— Systemic risk, financial network, financial contagion, financial resilience, financial reliability, locational marginal price (LMP).**

I. INTRODUCTION

A. Motivation

Since deregulation began in the 1990s, the electricity market (or power market) has experienced several significant reforms. The two-settlement clearing process has been widely adopted in electricity markets, and the locational marginal price (LMP) algorithm has been adopted to clear the market at the marginal cost of electricity at different locations [1]. Additionally, extensive financial products, such as virtual trading, have been integrated for risk hedging [3]. Various financial transactions in the electricity market thus support an economical and reliable grid operation.

However, the role of such heavily interconnected financial transactions in electricity markets can be controversial. Although the LMP algorithm and emerging financial products are expected to facilitate risk sharing and increase efficiency, the financial interdependence of electricity markets is becoming increasingly complicated such that the failure of particular participants to meet obligations may have significant consequences on overall market settlements. This receives increasing attention regarding financial risks due to the fast-growing renewable penetration which poses significant uncertainty into the market operation. In comparable financial systems like the banking system, the failure of Lehman Brothers at the beginning of the 2008 financial crisis immediately triggered a significant disruption in the banking system through chained reactions [4]. The severe profit loss of particular renewable owners due to forecasting errors may also diminish the profitability of other participants through the financial interdependency in the electricity market.

Therefore, without identification and analysis of the financial interconnections in the two-settlement electricity market, booming renewable penetrations could set the stage for potential *systemic* risk in the future. Previous renewable risk analysis in electricity market operation only focuses on managing *systematic* risk, i.e., the risk of a single participant or an operation. The risk interconnection, or systemic risk, has not been researched. In our previous work [1], the concept of systemic risk in electricity markets is proposed, and two risk indices of CoVaR and ΔCoVaR are constructed based on statistical properties. However, in [1], the focus is on the formulation of indices for risk connections, and there is a lack of foundational theory to analyze the root cause of the systemic risk. In this work, we are motivated to analyze systemic risk with a broader scope for the market clearing process and complete the financial properties and regulations of systemic risk in the two-settlement electricity market.

For a better illustration of systemic risk, new comparisons of systematic risk vs. systemic risk, as well as an analogy of them in power systems are proposed and shown in Table I. More discussion of systematic risk versus systemic risk can be found in our previous work [1].

Table I. Analogy of Systematic Risk and Systemic Risk

	Systematic Risk	*Systemic Risk*
Feature	An **external** shock causing the whole-society collapse of the financial system	A company-level collapse causing **a chained reaction** which eventually leads to significant financial losses of other players and even the collapse of the financial system
Example	1929-1933 financial crisis; World Wars	2008-2009 financial crisis (some companies are called "too big to fall")
Analogy to power systems	An **external** extreme event (e.g., a cyberattack or a natural disaster) causing simultaneous N-K failures & system collapse	A cascading failure which starts from a **critical single-component outage** gradually leading to losses of other components and even a blackout

B. Literature Review

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The U.S. has been shifting from traditional fossil fuel generators to renewable energy sources and aiming to achieve 80% renewable penetration by 2050 [5]. Increasing renewable penetration alters power grid operations significantly. Extensive research works have been conducted to facilitate reliable grid operation with high renewable generation. In [6], energy storage systems are deployed to support a stable renewable generation. In [7] and [8], demand response and energy storage are strategically deployed to address the intermittency of renewable generations. Further, managing the risk of renewable intermittency in market operations has become one of the most important concepts. In [9], a risk-averse joint offer strategy is proposed for aggregated wind producers participating in day-ahead market operations. In [10], a risk-cognizant economic dispatch model is proposed for market-clearing under high wind penetrations. In [11], a joint energy and reserve market model is proposed to reduce the risk of wind generation uncertainties by demand response. In [12], a risk-limiting dispatch was developed for market operations under high renewable penetrations. In [13], a bidding strategy for a concentrating solar power plant is proposed to deal with the risk of uncertain solar irradiations.

However, all the previous risk analysis views risk as an independent entity from either the operators' perspective or the participants' perspective. The risk connection, i.e., the systemic risk, in the electricity market with uncertainties is not well understood and researched. The concept of systemic risk in the electricity market is first proposed in our previous work [1]. This paper further develops the fundamental theory for the systemic risk in electricity markets under high renewable penetration for future root-cause analysis. The detailed contributions are presented in the next subsection.

C. Contributions

- This paper constructs a financial network for two-settlement electricity market operations, which allows decision makers to look beyond the financial interaction between adjacent or local nodes (financial wise, not physical) enabling further systemic risk analysis in the electricity market. Every market participant is considered as a node, and each financial transaction between two nodes is modeled with a weighted, directed link. The cash inflows and cash outflows describe the profitability of each market participant.
- This paper identifies a phenomenon of financial contagions in electricity market financial networks, which can impair the fairness of the market settlements. The increasing uncertainty due to the high penetration of renewables may exacerbate the financial contagions and lead to considerable systemic risk.
- This paper develops two financial properties, financial resilience and financial reliability, to evaluate the market settlements under high penetration of renewables, in terms of systemic risk. Although systemic risk has been investigated in the financial area, the electricity market systemic risk is not well-researched. The proposed concepts and properties of financial contagions, financial resilience, and financial reliability construct a theoretical foundation for electricity market systemic risk analysis such that further research works can be performed.

D. Paper Organization

The rest of this paper is organized as follows. In Section II, the electricity market financial network is proposed. Then, the concepts of financial contagions and systemic risk in an electricity market financial network are defined and analyzed. In Section III, the concepts of financial resilience and financial reliability in electricity market financial networks are proposed. Section IV demonstrates the proposed theoretical foundation of electricity market systemic risk on the Texas synthetic 2000-bus system under high renewable penetrations. Finally, conclusions and future works are discussed in Section V.

II. Concepts of Financial Networks and Financial Contagions in Electricity Markets

As discussed in Section I, the concept of systemic risk, which differs from systematic risk, has gained its popularity following the 2008 financial crisis, which occurred as a chain reaction of financial collapse stemming from the bankruptcy of Lehman Brothers. Unlike in the banking system, participants in the intra-day electricity market are mainly connected through the two-settlement clearing process which is supported by LMP calculations. Further, with emerging financial tools and mature market deregulations, the financial dependence between participants has become stronger. The growing penetration of renewables brings constant profitability variations and could germinate electricity market systemic risk which describes the risk interconnection or chained reaction among different entities in daily electricity market operations. In this section, first, the financial network in the electricity market is proposed. Then, the financial contagions in the electricity market financial network are defined and analyzed.

In summary, the proposed concepts extend and redefine the generic concept of systemic risk in finance to deal with electricity market operations. These new concepts in this and the next sections will serve as a theoretical foundation for future electricity market systemic risk analysis.

A. Electricity Market Financial Networks

A typical intra-day electricity market in the U.S implements a two-settlement process, where a day-ahead clearing settles the base generation, and a real-time clearing corrects the real-time deviation [14]. The detailed day-ahead and real-time market models can be found in [15].

Similar to a physical transmission network consisting of lines, capacitors, and transformers, financial transactions like biding/offering strategies and bilateral contracts construct a financial network in daily electricity market operations. In particular, every market participant is considered as a node, and the financial settlement between each node is considered as a weighted, directed link, which represents the monetary flow from a buyer to a seller. Note, electricity market transactions are settled at different time periods. Some payments are settled in days, and some payments are in months or years. The construction of the proposed financial network depends on the decision maker's preference. A typical monetary flow in a simplified two-settlement market, wherein electricity is viewed as a commodity, is shown in Fig.1.

Table II. Financial contagions of the PJM 5-bus system

Event A: 15% forecast error at Alta

	Profit loss (L)
Alta	180
PC	0
Bri	0

+

Event B: 15% forecast error at PC

	Profit loss (L)
Alta	0
PC	765
Bri	0

+

Event C: 15% forecast error at Bri

	Profit loss (L)
Alta	0
PC	0
Bri	2542.5

=

	Profit loss (L)
Alta	180
PC	765
Bri	2542.5

<

Event A, B, and C together

	Profit loss (L)
Alta	390
PC	1657.5
Bri	5508.8

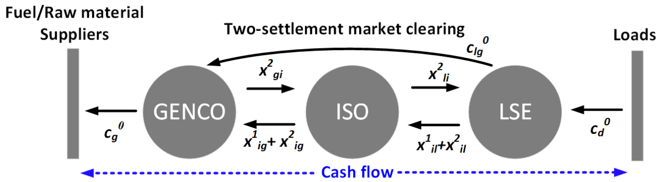

Fig. 1. Monetary flows in a simplified two-settlement market

Three time periods $t \in \{0,1,2\}$ are defined to represent pre-market preparations, day-ahead market-clearing, and real-time market-clearing. Let $x^{(t)}_{ij}$ denote the monetary circulation from market participant i to j at time t, and let $c^{(t)}_{ij}$ denote the payments outside the electricity market, which depends on external negotiations. GENCO, ISO, and LSE are indicated as g, i, and l. By this definition, GENCO's net cash flow N_{Gen} is shown in (1).

$$N_{Gen} = -c_g^{(0)} + c_{lg}^{(0)} + x_{ig}^{(1)} + x_{ig}^{(2)} + x_{gi}^{(2)} \tag{1}$$

If the day-ahead bidding is higher than the real-time generation, a real-time procurement $x^{(2)}_{gi}$ is enforced. If the day-ahead bidding is lower than the real-time generation, the excessive generation can also be used in real-time for regulation services. For a load serving entity (LSE), the net cash flow is shown in (2).

$$N_{LSE} = -c_d^{(0)} - c_{\mathrm{lg}}^{(0)} + x_{il}^{(1)} + x_{il}^{(2)} - x_{li}^{(2)} \tag{2}$$

From the scheme of the market-clearing process, all the cash flows at time 0 are independent, while the cash inflows/outflows of all participants at time 1 and time 2 are correlated by the LMP algorithm. The day-ahead market clears the base units and solidifies the profitability of market participants regardless of real-time variations. Therefore, the cash flows at time 1 are fixed before the delivery of commodities (electricity). At time 2, the cash flows are impacted by the uncertainties because the real-time market clears the deviations. Through the LMP algorithm, the net cash flows of all market participants are interconnected, which implies that some buses may not be connected physically, but there could exist financial links that interlink the participants located at those buses.

With a growing number of financial tools being used in electricity markets, such as virtual bidding, monetary circulation becomes much more complex and interconnected. Therefore, an imminent concern is that the uncertainty of renewables may impose an extensive financial shock, which may undermine the cash flow of all participants throughout the financial network. Therefore, understanding and managing systemic risk is an urgent task for further renewable integrations, especially in high penetration.

B. *Electricity Market Financial Contagions*

As shown in *Subsection A*, in the electricity market financial network, all participants are financially connected through the market-clearing process. Therefore, the net cash flow of each participant is interlinked with that of other participants. This interdependence implies that events that happen to particular participants can impact the profitability of others. In this paper, the event refers to real-time deviations, which lead to the payments for regulation services, but it could represent any financial shocks in an electricity market in general. For instance, malicious capacity withholding may lead to a wide-spread price spike and financial losses.

1) Definition of financial contagions in electricity market

Financial contagions typically refer to interlinks between payments of banks in a financial system [16] [17]. However, the financial system is characterized by voluntary monetary exchange, which emphasizes loan negotiations and the pursuit of future financial returns. The physical property of electric power intrinsically differs electricity market from conventional financial systems. Therefore, the concept of *electricity market financial contagions* is proposed with the following definition.

Electricity market financial contagions: the phenomenon that the financial losses of an electricity market participant, which is caused by a disturbance or uncertainty, may lead to financial losses of another market entity (e.g., a market player or the whole system) because of risk interconnections among different entities.

2) Illustration of financial contagions in electricity markets

An illustrative example with a modified PJM 5-bus system is shown in Fig. 2.

Three uncertainty events (A, B, and C) are modeled in Table II. In each event, only one participant deviates from the day-ahead forecast, and thus the regulation cost induced by such deviation is covered by the participant. However, when events A, B, and C happen together, the expensive fast-start (FS) unit must be dispatched. The LMP algorithm makes all participants pay at the marginal cost of the FS unit, as in the 4th table in Table II. Renewable farms Alta, PC, and Bri may argue that they should pay their own portions on the regulation services, as in the 3rd table in Table II because the cheap reserve is sufficient in each of the events (A, B, or C).

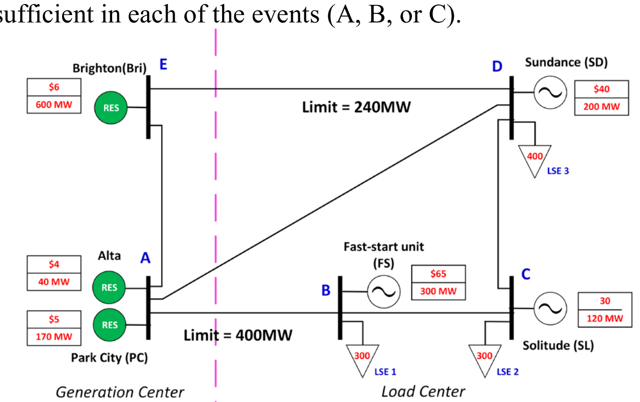

Fig. 2. PJM-5 bus system with 70% renewable penetration

The total uncertainty impact from different participants may generate more impact from the simple sum of individual uncertainties. This phenomenon indicates that the LMP algorithm makes all participants pay the marginal cost of the most expensive dispatched unit, even though some of them may not be the major reason for dispatching the expensive unit.

3) Explanations from electricity market operational perspective

From the electricity market operational perspective, the cheap reserve is not sufficient to cover all the deviations, and the expensive FS unit is likely dispatched.

$$L_i = MC^{FS} \times Dev_i \quad (3)$$

Note, the reserves are modeled only for the balancing power in the real-time market for simplicity to illustrate the concept. Therefore, the marginal cost of the FS unit MC^{FS} sets the LMP, and participants pay the regulation service L_i according to the deviation Dev_i, as in (3). However, the cheap reserve is sufficient when each of the three uncertainty events happens individually, and the payment to regulation service is settled by the marginal cost of the cheap unit, as in (4), which leads to a debate on who is responsible for the dispatch of the FS unit? Also, how can we fairly divide the responsibility among three units?

$$L_i = MC^{Cheap} \times Dev_i \quad (4)$$

As shown in the upper figure of Fig. 3, the uncertainty at each participant impacts the calculation of LMP, which in turn impacts the profitability of each participant.

4) Explanations from financial contagions' perspective

This paper explains this phenomenon from a financial contagion perspective. The profit loss of each participant affects the profit losses of other participants through the financial networks, as in (5). L_i^{self} represents the profit loss when unit i is the only unit with deviations, which is considered as the individual responsibility. As shown in Table II, the joint impact of multiple uncertainties may worsen the total profit loss of market participants than the simple sum of the impacts from individual deviations. The loss impact from other participants' uncertainties $L^{impact}{}_{i,j}$ demonstrates financial contagions in electricity market operations. Thus, the profit loss is divided into two parts: an individual responsibility term L^{self}, and a financial contagion term L^{impact}.

$$L_i = L^{self}{}_i + \sum_j L^{impact}{}_{i,j} \quad (5)$$

$$L^{impact}{}_{i,j} = \varphi_{i,j} L^{self}{}_i \quad (6)$$

$$L_i = L^{self}{}_i + \sum_j \varphi_{j,i} L^{self}{}_j \quad (7)$$

$$\varphi_{j,i} = f\left(\Delta CoVaR_q^{\sum_{i \neq j} L_i | L_j} \right) \quad (8)$$

$$\Delta CoVaR_q^{\sum_{i \neq j} L_i | L_j} = CoVaR_q^{\sum_{i \neq j} L_i | L_j = VaR_q} - CoVaR_q^{\sum_{i \neq j} L_i | L_j = Median} \quad (9)$$

The $L^{impact}{}_{i,j}$ can be further decomposed as in (6), where $\varphi_{i,j}$ represents the _financial contagion shift factor (FCSF)_. Similar to power transfer distribution factors, FCSF indicates the distributions of cash flow losses with respect to the financial losses at another entity in the market, so it is a unitless quantity showing the per-unit severity of financial contagion. Thus, (5) can be reformulated as (7) based on (6).

The benefit of analyzing events in the electricity market from a financial contagion's perspective is to provide a quantitative calculation of the financial impact on the market-clearing process. As shown in the lower figure of Fig. 3, the impact of individual participant's uncertainty on the profitability of other participants can be quantitatively measured through the shift factors of financial contagions.

The FCSF can be approximated through conditional regressions on the historical financial contagions between participants. The prevailing systemic indices, such as the marginal CoVaR (i.e., ΔCoVaR) in our previous work [1], can be applied to indicate the magnitude of shift factors. For example, to illustrate the magnitude of the shift factor of a particular participant on the rest of the participants, the marginal CoVaR can be obtained with (9), which represents the incremental profit loss of others when the profit loss of the particular participant increases from median value to VaR value. The value of the shift factor could be a function of marginal CoVaR, as shown in (8). A larger marginal CoVaR may correspond to larger shift factors. Detailed calculation and analytical model of the shift factor can be significant future works, while this paper mainly focuses on providing the concept and theoretical foundation of financial contagion for systemic risk analysis in the electricity market.

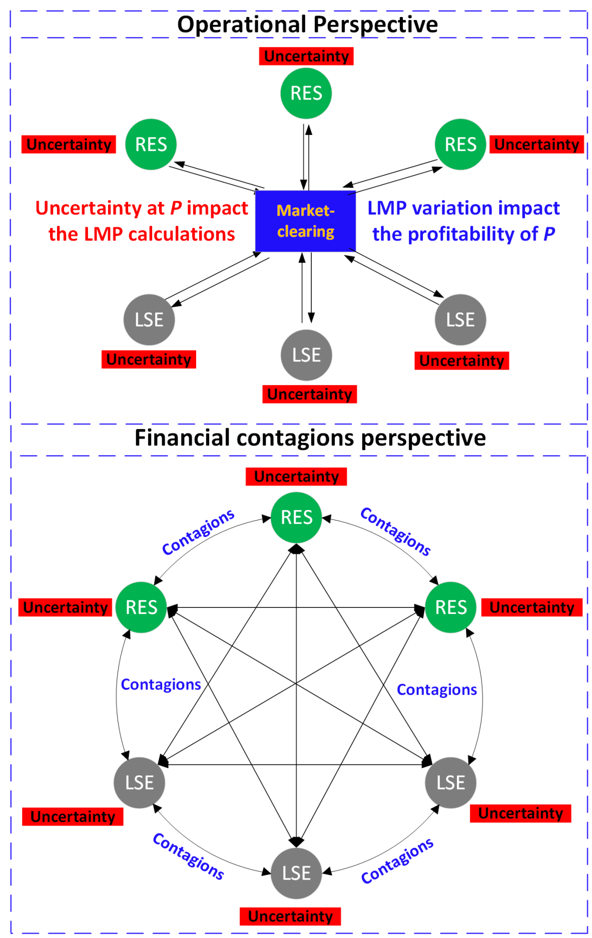

Fig. 3. Operational perspective and financial perspective of the phenomenon of financial contagions

If the prosumer can fulfill 100% of their responsibility in real-time as they bid in the day-ahead market, they are immune from financial contagions because the event in this paper is considered as real-time deviations. Note, this is not necessarily true for other types of events. Certainly, in practice, forecasts are generally imperfect with small variations, which means most participants must deal with financial contagions to some degree. Therefore, when the financial contagions are small ($L^{self}_{i} \gg \sum L^{impact}_{i,j}$), the market settlement is reliable. However, when the financial contagions significantly increase ($L^{self}_{i} \leq \sum L^{impact}_{i,j}$), the systemic risk in market operation emerges.

C. Illustration of Financial Contagion Shift Factor

Severe financial contagions could lead to systemic risk of significant financial losses. Considering another event D in the previous 5-bus system, when LSE 1 has a 5% real-time deviation, and RES owner Bri has 20% real-time deviations, LSE 1 and Bri pay \$975 and \$7345 for regulations, respectively. As shown in Table III, the financial contagion of Bri is 0.

Table III. Financial contagions lead to systemic risk

	L (\$)	L^{self} (\$)	L^{impact} (\$)	$\varphi_{i,j}$
LSE 1	975	450	525	0%
Bri	7345	7345	0	7.15%

However, the individual responsibility for LSE 1 is \$450, and it suffers a \$525 financial contagion from Bri. In this case, Bri is the main reason of dispatching the FS unit, but instead of letting Bri take the responsibility, the LSE 1 pays a lot more than its individual responsibility. In this event, participants who behave well suffer a loss due to the participants who behave poorly. If most of the well-behaved participants suffer significant financial contagions from few participants with very poor behavior (High value of FCSF), the systemic risk emerges. In this simple case, the FCSF can be directly calculated through linear equations, as in (10).

$$\varphi_{LSE\,1-Bri} = \frac{(L_{LSE\,1} - L^{self}_{LSE\,1})}{L_{Bri}} \tag{10}$$

The systemic risk in electricity market operations under renewable penetration describes the uncertainty of individuals leading to high profit losses of others, which, in the end, diminishes the fairness of the financial settlements. With high penetration of renewables and a more complicated system, the systemic risk becomes much more significant (see the case study in Section IV).

It should be noted that existing financial instruments like financial transmission rights (FTRs) can mitigate the risk of a high-cost scenario. However, they do not illustrate the risk connections and severity of the risk in a given system, while financial resilience and financial reliability based on contagion give a proper signal about how severe the financial risk can be. Thus, financial resilience and reliability can provide guidelines for market participants to properly evaluate their risk level for a single extreme event or the average case.

III. Concepts of Financial Resilience and Financial Reliability of Electricity Markets

In this section, two financial properties considering uncertainties, financial resilience (FRES) and financial reliability (FREL), are defined and discussed. With the proposed two financial properties, the financial contagions and systemic risk spread in two-settlement electricity market operations are analyzed. Then, simple and illustrative examples in the modified PJM 5-bus system are presented.

In power systems, resilience refers to the ability of the grid dealing with low probability but high impact events (e.g., hurricane). Reliability refers to the ability of the grid restoring to normal operation for any disruptions on average. With a similar analogy, financial resilience and financial reliability are proposed for electricity market financial health assessments for extreme events and average events, respectively.

A. Electricity Market Financial Resilience

1) Definition of electricity market financial resilience

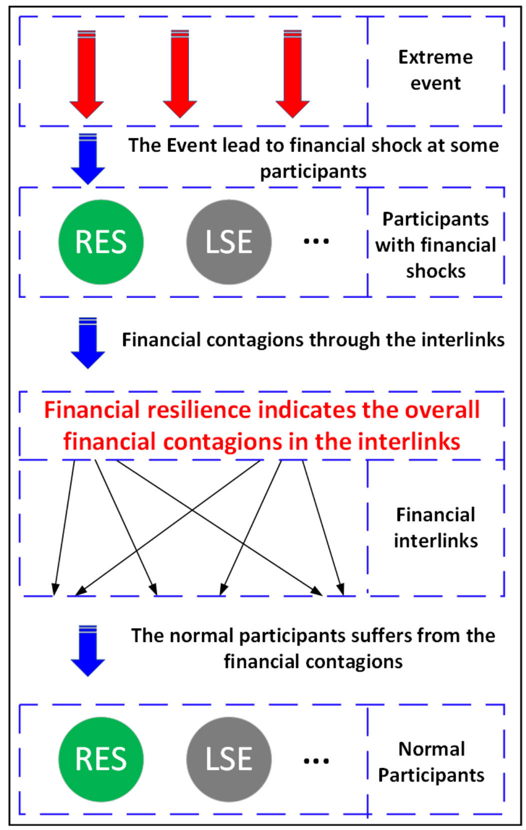

Fig. 4. Concept of financial resilience for electricity market

Similar to power grid resilience which characterizes the ability of the physical grid responding to extreme events such as natural disasters, the proposed electricity market financial resilience emphasizes the ability of electricity market financial network responding to extreme financial shocks. The definition of financial resilience is given as follows:

Electricity market financial resilience: The ability of the electricity market dealing with the low probability but high impact events (e.g., large capacity-withholding).

This paper focuses on electricity market systemic risk, where financial health is mainly evaluated by financial contagions. Therefore, financial resilience signals the extent of financial contagions under an extreme event. Particularly, a loss or huge forecast error of several large renewables could induce a catastrophic financial shock in the market-clearing process. As shown in Fig. 4, if there is an extreme event leading to financial shocks at some participants, then the financial interlinks will spread financial contagions in the market settlements, which impact the profitability of other participants. The financial resilience will indicate the severity of the financial contagions due to the extreme event.

2) Evaluation of electricity market financial resilience

Based on the above definitions and clarifications, a general financial resilience (FRES) index υ^{res} is formulated as in (11), which measures the proposed financial resilience in electricity market settlements. It represents the sum of profit loss L of all market participants under the extreme event versus the sum of individual responsibilities L^{self} of all market participants. Therefore, under an extreme event, the higher financial contagions, the larger the index υ^{res} is. Similar to (5), the sum of L can be divided into the sum of L^{self} and the sum of financial contagions L^{impact}, as shown in (12). Thus, (11) can be reformulated as (13) where the second term indicates the percentage of financial contagions over the sum of L^{self}. Further, (13) can be reformulated as (14) with a new variable ρ_j which represents the share of L_i^{self} in $\sum L_j^{self}$. Thus, aligned with the financial resilience definition, the FRES index ν^{res} evaluate the resilience of electricity market financial network structure because $\varphi_{j,i}$ represent the financial interlinks, and ρ_j indicates the magnitude of individual responsibility under the extreme event.

$$\nu^{res} = \frac{\sum_i L_i}{\sum_i L^{self}{}_i} \mid \text{Extreme} \tag{11}$$

$$\sum_i L_i \mid \text{Extreme} = \sum_i L^{self}{}_i + \sum_i \sum_j L^{self}{}_j \varphi_{j,i} \mid \text{Extreme} \tag{12}$$

$$\nu^{res} = 1 + \frac{\sum_i \sum_j L^{self}{}_j \varphi_{j,i} \mid \text{Extreme}}{\sum_i L^{self}{}_i \mid \text{Extreme}} \tag{13}$$

$$\nu^{res} = 1 + \sum_i \sum_j \frac{\varphi_{j,i}}{\rho_i} \mid \text{Extreme} \tag{14}$$

B. Electricity Market Financial Reliability

1) Definition of electricity market financial reliability

Similar to power grid reliability which refers to the ability of the system to deliver expected services, such as the total interruptions in a year, the proposed electricity market financial reliability emphasizes the financial health of electricity market on average over a period of time. The definition of financial reliability is given as follows:

Electricity market financial reliability: The ability of the electricity market responding to the average disturbances over a period of time (e.g., daily renewable variations).

From the systemic risk perspective, financial health is mainly determined by financial contagions. The financial reliability of the electricity market network will indicate the average financial contagions in market settlements from a probabilistic perspective. For each operation day, events or disturbances may happen, including extreme events and normal events, and most of the events are not severe which may only contain small financial contagions. If compared with the financial resilience which emphasizes an individual extreme event and leads to extensive financial contagions, the proposed financial reliability focuses on the variations of financial contagions over a period of time with a probabilistic model, as shown in Fig. 5.

From the financial reliability perspective, it is worth noting that, for some participants who suffer a large value of financial contagions L^{impact} all the time, the total value of profit loss L of the participant tends to be sensitive to others' deviations and insensitive to their own deviations. For some participants who generally suffer a small value of financial contagions L^{impact}, the profit loss mainly depends on their own deviations.

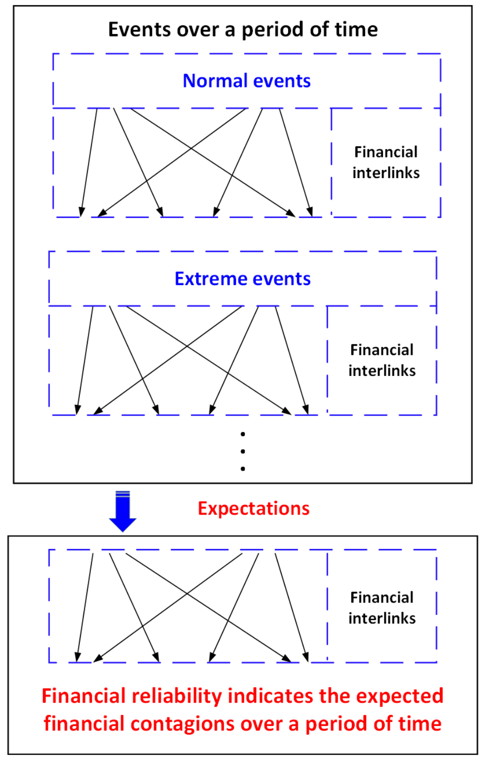

Fig. 5. Concept of financial reliability for electricity market

2) Evaluation of electricity market financial reliability

$$\nu^{rel} = \frac{\sum_i L_i}{\sum_i L^{self}{}_i} \mid \text{Expectation} \tag{15}$$

$$\sum_i L^{self}{}_i \mid \text{Expection} = \sum_i \int L^{self}{}_i dF \tag{16}$$

$$\sum_i L_i \mid \text{Expection} = \sum_i \int L_i dF \tag{17}$$

$$\sum_i L_i \mid \text{Expection} = \sum_i \int L_i^{self} dF + \sum_i \sum_j \int L^{self}{}_j \varphi_{j,i} dF \tag{18}$$

Based on the above definitions and clarifications, a general financial reliability (FREL) index ν^{rel} is formulated in (15), which represents the sum of expected profit loss L of all market participants versus the sum of expected individual responsibility L^{self} of all market participants. The reliability index aims to measure the expected financial contagions in the settlement over a period of time. With enough historical samples, a probability distribution F can be approximated for all the events. This paper focus on the event of real-time deviation which is generally not constant and follows a probabilistic distribution, and excessive renewable generations (i.e., positive deviations) are considered with a 0 financial contagion. Equations (16) and (17) describe the calculation of the expected value of L and L^{self} over the distribution F. Further, similar to (5), the expected value of L can be decomposed to the expected L^{self} and expected L^{impact}, as in (18).

Then, (15) can be reformulated as (19), where the second term indicates the percentage of the expected financial contagions over the sum of expected individual responsibility L^{self}. Similar to (14), the relationship between the FREL index ν^{rel} and contagions shift factor is formed in (20). Thus, aligned with the financial reliability definition, the index ν^{rel} evaluate the expected financial contagions in the financial network. If we compare the reliability index ν^{rel} in (20) with the resilience index ν^{res} in (14), ν^{res} measures the financial contagions of a specific extreme event, while ν^{rel} evaluates financial contagions over a probability distribution which contains both normal events and extreme events.

$$\nu^{rel} = 1 + \frac{\sum_i \sum_j \int L^{self}{}_j \varphi_{j,i} dF}{\sum_i \int L_i^{self} dF} \tag{19}$$

$$\nu^{rel} = 1 + \sum_i \sum_j \int \frac{\varphi_{j,i}}{\rho_i} dF \tag{20}$$

C. Illustration of FRES and FREL in the PJM 5-bus system

To further clarify the above two financial properties, they are exemplified via the previous modified PJM-5 bus system. Without loss of generality, we assume that the market operator decides the risk tolerance of resilience and reliability in this system are 200% and 150% based on past experiences. The tolerance thresholds can be adjusted by decision makers in real-world practice based on operators' experience. This is aligned with the power system (physical) resilience or reliability criterion in utility practices.

1) Financial resilience example

An extreme event is considered in which 15% forecast errors occur at all three renewable farms (Alta, PC, and Bri), while other participants have normal variations which are assumed to be 5% deviations. Then, the value of profit loss L, individual responsibility L^{self}, and financial contagions L^{impact} are obtained, as shown in Table IV.

Table IV. Financial contagions under the extreme event

	L^{self} (\$)	L (\$)	L^{impact} (\$)
LSE 1	450.00	975.00	525.00
LSE 2	450.00	975.00	525.00
LSE 3	600.00	1300.00	700.00
Alta	180.00	390.00	110.00
PC	765.00	1657.50	892.50
Bri	2542.50	5508.80	2966.30
Sum	**4987.50**	**10806.30**	**5718.80**

Then, the resilience index can be calculated with Eq. (7), which gives ν^{res} = 216.67% (=10806.3/4987.5). Thus, in this extreme event, the sum of profit loss L is 216.67% of the sum of the individual responsibility. In other words, the sum of financial contagions is 116.67% over the sum of individual responsibility. If compared with the pre-defined resilience threshold of 200%, the market settlement is not financially resilient because 216.67% > 200%. It should be noted that the marginal costs of the reserves directly impact the severity of the financial contagions. If all the reserves in the system have the same price (even if it is high), then financial contagions disappear. In this case that there is only one cheap reserve and one expensive reserve, and the cheap reserve can cover all deviations individually but cannot cover the sum of all deviations, the FRES index is simply equal to the marginal cost of the expensive reserve divided by the marginal cost of the cheap reserve.

2) Financial reliability example

The real-time deviation distributions for load and renewables are constructed based on [20] to simulate the continuous happening events. The LSE 1~3 and the three renewable resources in the previous 5-bus system are assumed to follow the normal distribution, as shown in Fig.6.

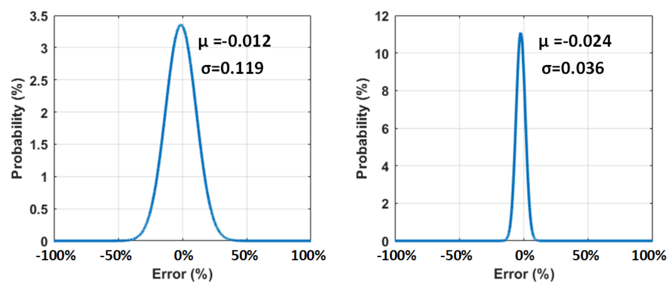

Fig. 6. Deviation distribution for renewables and LSEs

Thus, the expected value of profit loss L, individual responsibility L^{self}, and financial contagions L^{impact} are obtained for all market participants, respectively, as shown in Table V.

Table V. Expected financial contagions

	L^{self} (\$)	L (\$)	L^{impact} (\$)
LSE 1	270.99	411.18	140.19
LSE 2	270.99	411.18	140.19
LSE 3	298.71	548.24	249.53
Alta	105.25	194.40	89.16
PC	447.29	606.22	158.93
Bri	2011.63	2746.05	734.42
Sum	**3404.86**	**4917.27**	**1512.42**

The FREL index, ν^{rel}, is obtained as 144.22% (=4917.27/3404.86), which means that the sum of the expected profit loss L is 144.22% of the sum of the expected individual responsibility L^{self}. The expected financial contagion L^{impact} is 44.22% of the sum of the expected L^{self}. If compared with the pre-determined threshold of 150%, the market settlement is financially reliable (144.22%<150%). It is worth noting that, for this system, the financial contagions are generally from the renewable Bri and PC to the rest of participants because other participants suffer more from financial contagions, while the L^{impact} for Bri and PC is relatively small, in terms of percentage.

IV. Case Study in Texas Synthetic 2000-bus System

The previous small test system (PJM 5-bus system) is presented in Section II and Section III to help clarify the proposed concepts of financial contagion, financial resilience, and financial reliability in electricity markets with uncertainties. In this section, a Texas synthetic 2000-bus system is considered to demonstrate the proposed theoretical foundation under high renewable penetration for a large system. The system parameters can be found in [18] and [19], and the renewable penetration is increased to 70%. The cost data of generators are modified to different levels. Further, the market operator decides the risk tolerance of resilience and reliability in this system are assumed to be 250% based on past experience of the decision makers.

A. Severity and Spread of Systemic Risk under High Renewable Penetration

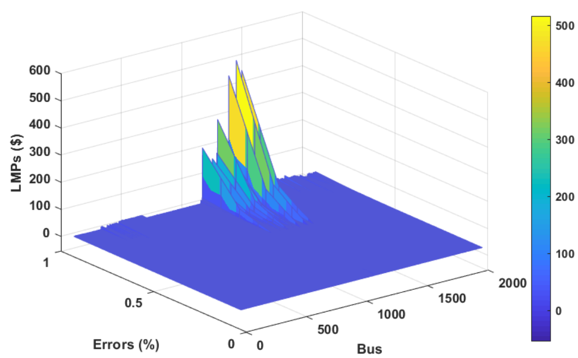

Fig. 7. LMP incremental due to low-quality renewables.

To demonstrate the spread of systemic risk, an extreme event is considered such that 5 low-quality renewable farms have sudden extra forecast errors, while all other high-quality participants behave normally, which means 2% and 3% deviations for LSEs and renewables, respectively. Fig. 5 shows that the LMPs at buses of high-quality participants are inevitably increased due to the deviation at those 5 low-quality renewable farms. Further, with more severe deviations at the 5 low-quality renewable farms as shown in the "Error (%)" axis of Fig. 7, the high-quality participants suffer more from financial contagions.

In particular, at bus 1344, LMP jumps from \$19 to \$516. However, the renewables and loads at bus 1344 behave normally at 2% and 3% deviations. Instead of letting the renewable farms of low-quality be responsible for dispatching the expensive fast-start unit, the market-clearing process makes all participants pay at the marginal cost of the expensive fast-start unit. As such, the low-quality renewables spread financial contagions to the normal participants.

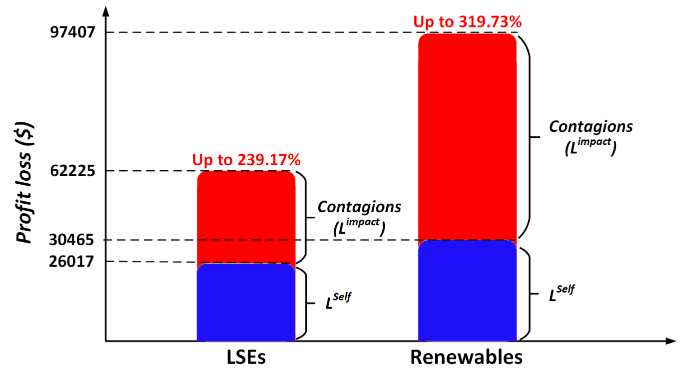

Fig. 8. Financial contagions due to the low-quality renewables.

The extent of financial contagions is shown in Fig. 8. If compared to the financial contagions in standard case, the 5 low-quality renewable farms can lead up to 239.17% and 319.73% financial contagions for normal LSEs and normal renewables. The financial contagions could be more severe for particular participants, such as participants at bus 1344. Therefore, the phenomenon of financial contagions could be significant under extreme events.

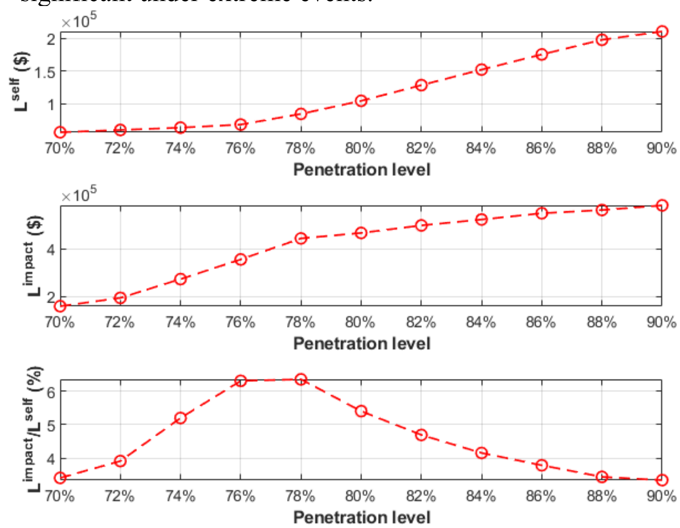

Fig. 9. Financial contagions under different renewable penetration levels.

Further, a higher renewable penetration level brings higher uncertainties, which impact the value of LMPs and the financial contagions. Fig. 9 shows the overall financial contagions under different renewable penetration levels from 70% to 90%. The value of individual responsibility (L^{self}) increases from \$56,482 to \$210,501, as shown in the first figure in Fig. 9. Higher uncertainties of each participant lead to more reserve cost for themselves, which escalates the value of L^{self}. The value of financial contagion (L^{impact}) also increases from \$159,632 to \$583,410, as shown in the second figure in Fig. 9. The value of financial contagion increases accordingly with the increase of renewable penetrations because higher uncertainties from some participants drive up the reserve price leading to higher reserve costs for other participants. However, a higher value of L^{impact} does not necessarily mean a higher systemic risk. The systemic risk emerges when well-behaved participants suffer significantly from poorly-behaved participants, as discussed in Section II.B. As shown in the third figure in Fig. 9, the ratio of

L^{impact} over L^{self} increases initially and then decreases, which means the average value of FCSF does not necessarily increase with renewable penetration levels. The severity of systemic risk always depends on the relationship between L^{impact} and L^{self}. The next subsection will further indicate the extent of systemic risk by constructing and calculating the FRES and FREL indices.

B. Financial Resilience and Financial Reliability of the Synthetic Texas System

To provide a realistic setting, the real-time deviation distribution for renewables and loads in the ERCOT system is modeled based on [20]. The distributions have been provided in Fig. 6. Further, to account for the difference for various renewable sites, a small random bias (0% - 3%) is also added as noise which follows a uniform distribution. Then, three thousand samples are generated based on the above distributions to represent the continuously happening events over a period of time.

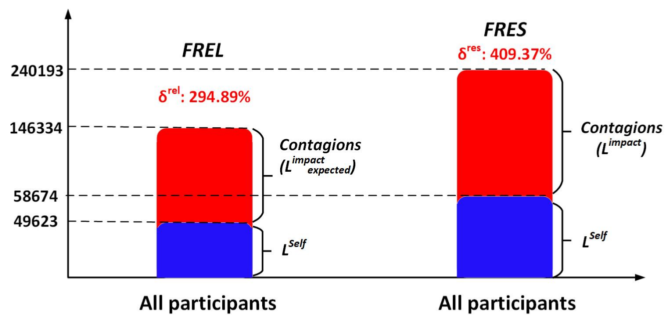

Fig. 10. Value of the FRES and FREL indices.

To assess the financial resilience, an extreme event is considered in which 30% renewables reach their 95% VaR value of the deviations, while the rest of the renewables are assumed within 3% deviations, and LSEs are assumed to have 2% deviations. The FRES index is obtained as 409.37%, shown by the left bar in Fig. 10. The profit loss of all participants due to the financial contagions L^{impact} is 409.37% with respect to the individual responsibility L^{self}. Thus, under this extreme case, market participants suffer 309.37% financial contagions. If compared with the pre-determined threshold based on decision maker's operational experience (i.e., 250%), the market settlement is not financially resilient.

Similarly, to assess the financial reliability, the expected profit loss of all participants over the three thousand samples is obtained, and the FREL index is calculated as 294.89%, shown by the right bar in Fig. 10. This means that market participants are expected to suffer 194.89% financial contagions. If compared with the pre-determined financial reliability threshold (i.e., 250%), the market settlement is not financially reliable because 294.89% > 250%. It should be noted that the severity of the systemic risk is closely related to the difference in the marginal cost of the reserves. With the development of cheaper reserves, the systemic risk could be reduced gradually.

V. Conclusion

In summary, this paper has established a theoretical foundation for electricity market systemic risk analysis, which can serve as the cornerstone for further systemic risk studies, especially under future high penetration renewables as demonstrated by the 70% renewable case study. First, a financial network is proposed for monetary circulation analysis in market operations under high-penetration renewables. Second, the phenomenon of financial contagions is identified, defined, and analyzed in detail; and the FCSF is presented to illustrate the severity of systemic risk. Third, two financial properties, financial resilience, and financial reliability, for electricity market systemic risk analysis under renewable uncertainties are defined, and indices are proposed to quantify these two properties. The proposed concepts and properties are illustrated in detail on the PJM 5-bus system modified with three renewable plants. Finally, the Texas synthetic 2000-bus system with 70% renewable penetration is employed to demonstrate the proposed theory of systemic risk models.

In our vision, the proposed new concepts of financial resilience and financial reliability based on financial contagion in systemic risk assessment opens a new direction of modeling the financial interconnections among different players in electricity markets. There are a number of areas of future works which are elaborated as follows.

- The impacts of various financial products on the potential systemic risk can be investigated, and a systemic-risk-averse market-clearing structure is necessary.
- The ultimate goal of our work on regulating systemic risk is to fairly divide the responsibility of participants with uncertainties that may drive high LMPs. This fair division can be investigated in the future.
- Financial resilience and financial reliability may provide input signals to other financial instruments such as FTRs and show how severe the potential financial impacts (losses) to different entities can be. Thus, they provide guidelines for decision makers to choose proper FTR protection.
- Another challenge to address is to develop a generalized approach to define extreme events or to find thresholds of financial resilience and financial reliability in a specific system.
- The discussion in this work focuses on the forecast errors while future works can be expanded to model spatial and temporal correlations of uncertain events, as well as many natural disasters or extreme weather events.
- Implication of the most recent Texas 2021 Blackout is that part of the blame goes to the Texas energy-only market mechanism, which fails to incentivize the generations to provide a reliable system. Essentially, the proposed systemic risk framework helps the market operators properly incentivize the market participants considering the responsibility allocations under extreme events, instead of purely relying on the price spikes.

VI. Acknowledgement

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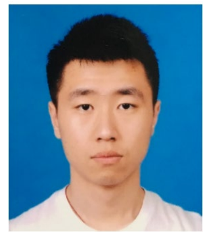
BIOGRAPHIES



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