Supplemental Information

Comparison of day-ahead and real-time transmission value

Real-time transmission value is significantly greater than day-ahead value, yet average electricity prices are lower in the real-time market (see left panel of Figure 9). Transmission value is not only greater in the real-time market on average, but for the vast majority of links each year, as shown by the “Links” line on the center panel of Figure 9. It would be natural, then, to expect that most hours see a transmission value increase when moving from the day-ahead market to the real-time market; yet this is not the case. The “Hours” line on the center panel of Figure 9 hovers near 50%, meaning that a link’s market value is approximately equally likely to increase or decrease from the day-ahead to the real-time market for any given hour. Specifically, from 2012 through 2020, the transmission market value was greater in real-time between 46.2% and 47.4% of the time. This quantity experienced an uptick in 2021 that continued through 2022 with 49.9% and 50.6% of hours, respectively, seeing an increase in transmission value moving from the day-ahead to real-time markets.

It is the magnitude of the change in transmission value between markets that primarily drives greater real-time value. The right panel of Figure 9 shows that, in each year, the mean increase in transmission value from day-ahead to real-time (darker line) is greater than the mean decrease (lighter line). The difference is significant; the average increase is at least twice the average decrease in all years except 2021.

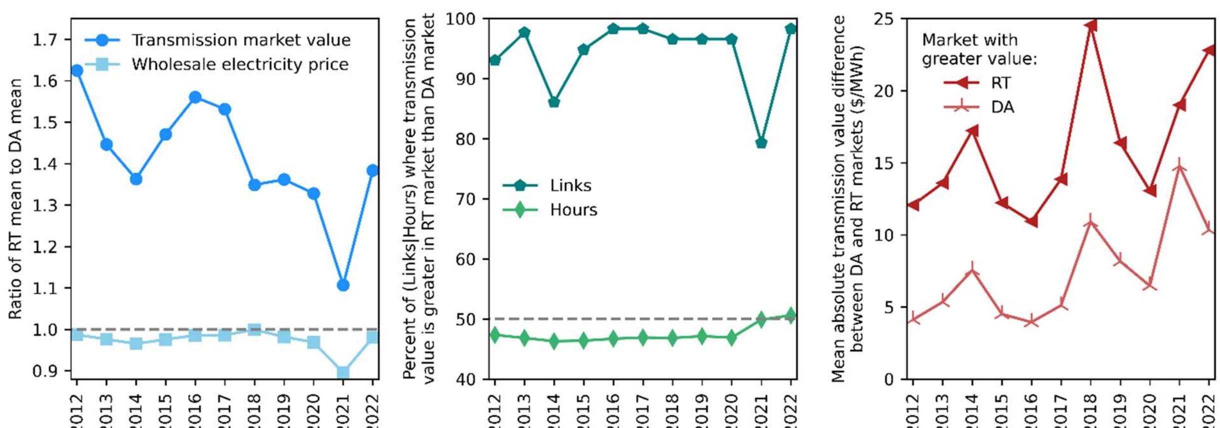

Figure 9 Comparison of transmission market value in day-ahead and real-time markets. Excludes links connected to the non-ISO West. The set of links in the early years is smaller due to data constraints.

Conditions during times of peak transmission value

Hot weather was found to have a limited relationship with transmission value and typically impacts peak transmission value periods by driving high net load. Of the hottest 5% of days in each location, 7% of hours overlap with the peak value hours suggesting that a hot weather hour is only 2 percentage points more likely to experience peak transmission value than an hour picked at random. However, the hottest 1% of days in each location show a stronger relationship with transmission value: 10% of hours on these days overlap with peak value hours. Nearly all of these high-heat peak-value hours and their associated transmission value overlap with unforeseen events, high renewable generation, or high net load conditions (89% of hours, 95% of value). Because including hot weather as a stand-alone condition would only decrease the proportion of transmission value labeled "None of the Above" in Figure 5a by 0.001, we do not focus on it in our results.

Some of the peak value occurs during specific events known to have impacted the electricity grid, but most is found outside of these extreme events. We find that these designated events, defined as key weather events identified in the literature (e.g., named storms, heatwaves) or as periods of grid stress identified by the North American Electric Reliability Corporation (NERC), are present for 11% of peak value hours, representing 21% of total value during peak value hours. See Table 3 for a list of designated events. The impact of these events is generally already captured by the other underlying conditions discussed in this section, to the extent that including these designated events would only decrease the proportion of transmission value labeled "None of the Above" in Figure 5a by 0.003. Such a result suggests that transmission value is driven by more routine instances of uncertainty and cold snaps, rather than by historic reliability events documented by NERC or caused by memorable storms.

	Percentage of time condition overlaps with peak transmission value, where peak is defined as the top __ of hours			**Percent of all hours**
	1%	**5%**	**10%**	
Unforeseen intraday variance	12.9%	43.2%	58.1%	6.7%
High net load (highest 5%)	4.1%	13.3%	22.0%	5.7%
Cold weather (coldest 5%)	3.7%	13.1%	21.3%	6.2%
Hot weather (hottest 5%)	1.9%	7.3%	13.1%	7.0%
Hot weather (hottest 1%)	2.9%	9.9%	17.0%	1.6%
High renewable generation (highest 5%)	1.4%	9.5%	20.4%	6.3%
Designated events	3.4%	10.6%	17.7%	5.3%

Table 2 Summary of analyzed system conditions: prevalence and impact on peak transmission value (real-time). Aggregate results for all 52 studied links within or between ISO or RTO regions, excluding those in the non-ISO West and Southeast.

Geographic differences in conditions during times of peak transmission value – two case studies

Between PJM_VA and MISO_INHub there is an average price difference of $14/MWh, equivalent to an average marginal value of $125 million per year for a 1 GW link during the 11-year study horizon. At least one of the four key conditions is present for over 96% of peak transmission value. At 81%, unexpected events are the most prevalent condition, but most unexpected events occur at the same time as at least one of the other conditions. The coldest days correspond to 45% of the peak value and regularly include high net load hours, presumably driven by heating demand. 11% of peak value occurs when renewable generation is at its highest levels; typically there is also an unexpected event during these hours. Figure 11 depicts these findings.

Within SPP, an east-west link across Kansas has an average price difference of $20/MWh, equivalent to an average marginal value of $174 million per year for a 1 GW link over the 11-year study horizon. Here, unexpected events and high renewable generation are the key conditions present during peak transmission value periods. An unexpected event occurred during 77% of peak transmission value, with limited overlap with other studied conditions. High renewable generation, present for 20% of peak value, is the second-most prevalent condition. Figure 10 depicts these findings. There is a persistent pricing gradient between these nodes, with the real-time price at the eastern node higher than that at the western node for 82% of the studied hours and 91% of the transmission value. When renewable generation in SPP is near its peak (in the top 5%), the direction of the pricing differential is even more predictable: the price is higher in the east for 97% of the hours and 99% of the transmission value. This pattern is consistent with the high penetration of wind generation in western SPP depressing prices there (median price of -$15.62 during high renewable generation versus $18.55 overall) while prices on the eastern side of Kansas are above typical levels (median price of $33.26 during high renewable generation versus $24.67 overall) despite the surplus of low marginal cost generation on the other side of the transmission constraints.

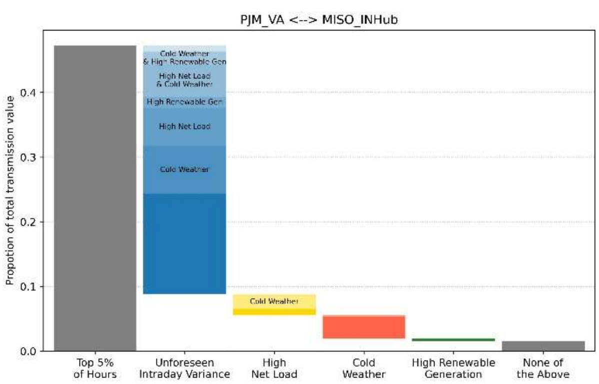

Figure 11 Contribution of key system conditions to the marginal transmission market value during peak hours of a link between PJM's Dominion Hub and MISO's Indiana Hub.

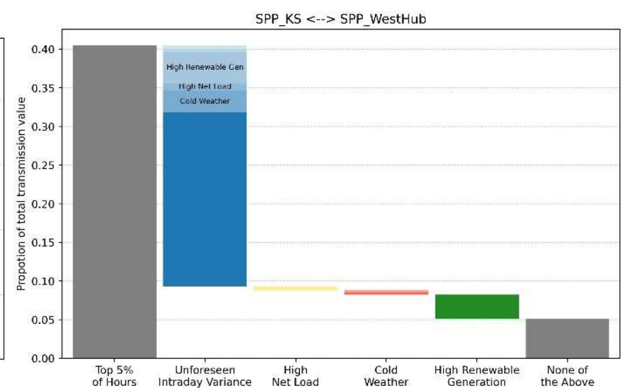

Figure 10 Contribution of key system conditions to the marginal transmission market value during peak hours of an east-west link across Kansas.

Transmission costs compared to market value

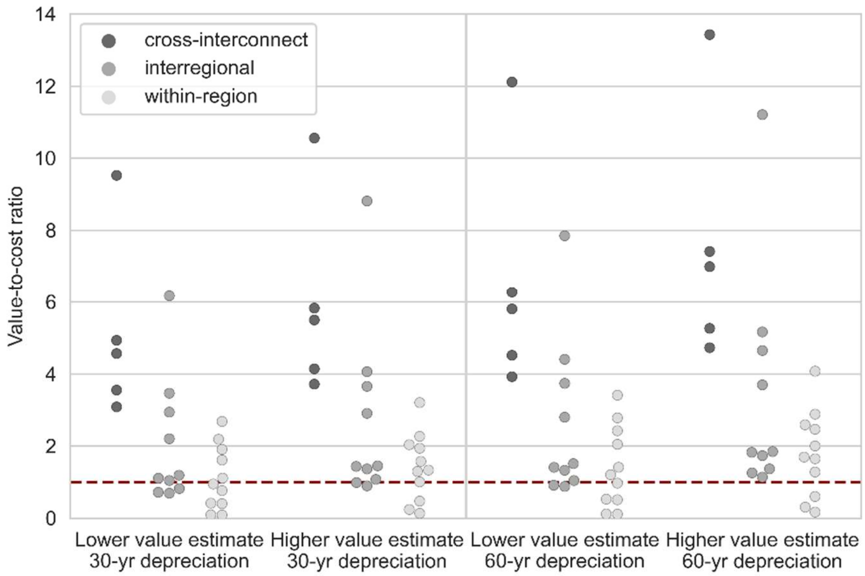

Figure 12 Comparison of project costs to market value estimates that account for market depth under different choices of value estimate and depreciation rate.

Supplemental Information about Methods

Algorithm 1 Transmission value estimates accounting for market depth based on supply curve models

Require: Non-decreasing supply curve functions: $\{f^s_\tau\}_{s\in\text{PriceNodes},\tau=1,2,\ldots,(\#\text{ of periods})}$
Require: Data on net load, prices, and transmission capacity for each hour and each link $a \leftrightarrow b$:
$DATA = \{(\text{NetLoad}^{Node\ a}_t,\ \text{Price}^{Node\ a}_t,\ \text{NetLoad}^{Node\ b}_t, \text{Price}^{Node\ b}_t,\ \text{Transfer Capacity},\ \text{Period containing } t)\}$
Require: Price caps such that trade is assumed to be 0 if cap is met at both nodes: $\{cap^s\}_{s\in\text{PriceNodes}}$
Require: Parameters defining tolerance on residuals and for use in screening models:
Maximum acceptable absolute residual: Δ_1
Maximum acceptable multiple of the median absolute deviation from the median: Δ_2
Threshold for screening models (minimum proportion of points within acceptability buffer): Γ
▷ In this paper $\Delta_1 = \$25$, $\Delta_2 = 2$, and $\Gamma = 2/3$

$\{X^s_\tau\} = \{\{x^s_t \mid (x^s_t, \ldots, \tau^*) \in DATA\}_{\tau^*=1,2,\ldots,(\#\text{ of periods})}\}_{s\in\text{PriceNodes}}$ ▷ net load data
$\{Y^s_\tau\} = \{\{y^s_t \mid (\ldots, y^s_t, \ldots, \tau^*) \in DATA\}_{\tau^*=1,2,\ldots,(\#\text{ of periods})}\}_{s\in\text{PriceNodes}}$ ▷ price data
$\{T_s\}, \{P_s\} \leftarrow \text{ScreenModels}(\{f^s_\tau\}, \{(X,Y)^s_\tau\}, \Delta_1,\ \Delta_2,\ \Gamma)$ ▷ hours and periods with a usable model
$\{\tau^s_+,\ x^s_+,\ \tau^s_-,\ x^s_-\}_{s\in\text{PriceNodes}} \leftarrow \text{SteepestSlope}(\{f^s_\tau \mid \tau \in P_s\}, \{X^s_\tau \mid \tau \in P_s\})$
for all $(x^a_t, y^a_t, x^b_t, y^b_t, \ell, \tau) \in DATA$ **do**
  for $s \in \{a, b\}$ **do**
    $tol^s_\tau = \max\{\Delta_1,\ \Delta_2 \cdot \text{Median}_{y\in Y^s_\tau}\left(|y - \text{Median}_{y\in Y^s_\tau}(y)|\right)\}$
    if $t \in T_s$ **and** $|y^s_t - f_{s,\tau}(x^s_t)| \le tol^s_\tau$ **then**
      $\lambda_s = 0$
      $\delta^s_t = \text{argmin}_{\delta\in\mathbb{R}:\ f^s_\tau(\delta)=y^s_t} |x^s_t - \delta|$
      $g^s_t(z) := f^s_\tau\left((\delta^s_t + x^s_t)/2 - x^s_t + z\right) + y^s_t - f^s_\tau\left((\delta^s_t + x^s_t)/2\right)$ ▷ translated supply curve
      if $\min\{g^{s\prime}_t(z) \mid z \in [x^s_t - \ell,\ x^s_t + \ell]\} < 0$ **then** ▷ translated supply curve is decreasing near x^s_t
        $\lambda_s = 2$
        $h^s_t(z) := f^s_\tau(z) + y^s_t - f^s_\tau(x^s_t)$ ▷ vertically translated supply curve
        if $y^s_t \ge \text{Median}_{y\in Y^s_\tau}(y)$ **then** $g^s_t(z) := f^s_{\tau^s_+}(x^s_+ - x^s_t + z) + y^s_t - f^s_{\tau^s_+}(x^s_+)$ ▷ translated steep supply curve
        else $g^s_t(z) := f^s_{\tau^s_-}(x^s_- - x^s_t + z) + y^s_t - f^s_{\tau^s_-}(x^s_-)$ ▷ translated steep supply curve
    else
      $\lambda_s = 1$
      if $y^s_t \ge \text{Median}_{y\in Y^s_\tau}(y)$ **then** $g^s_t(z) := f^s_{\tau^s_+}(x^s_+ - x^s_t + z) + y^s_t - f^s_{\tau^s_+}(x^s_+)$ ▷ translated steep supply curve
      else $g^s_t(z) := f^s_{\tau^s_-}(x^s_- - x^s_t + z) + y^s_t - f^s_{\tau^s_-}(x^s_-)$ ▷ translated steep supply curve
      if $t \in T_a$ **then**
        $\lambda_s = 2$
        $h^s_t(z) := f^s_\tau(z) + y^s_t - f^s_\tau(x^s_t)$ ▷ vertically translated supply curve
  $c^{a,b}_t(z) := \mathbf{1}[y^a_t > y^b_t](g^a_t(x^a_t - z) - g^b_t(x^b_t + z)) + \mathbf{1}[y^a_t \le y^b_t](-g^a_t(x^a_t + z) + g^b_t(x^b_t - z))$
  $\ell' = \min\{z \mid c^{a,b}_t(z) = 0,\ z \in \mathbb{R}^+\}$ ▷ transfer capacity saturation point
  $v = \int_0^{\min\{\ell,\ell'\}} c^{a,b}_t(z)\,\mathrm{d}z$ ▷ transmission value estimate
  if $\lambda_a \in \{0, 1\}$ **and** $\lambda_b \in \{0, 1\}$ **then** $\underline{v}^{a,b}_t = \bar{v}^{a,b}_t = v$
  else
    if $\min\{\lambda_a, \lambda_b\} \le 1$ **then**
      if $\lambda_b == 2$ **then**
        $c^{a,b}_{t,2}(z) := \mathbf{1}[y^a_t > y^b_t](g^a_t(x^a_t - z) - h^b_t(x^b_t + z)) + \mathbf{1}[y^a_t \le y^b_t](-g^a_t(x^a_t + z) + h^b_t(x^b_t - z))$
      else
        $c^{a,b}_{t,2}(z) := \mathbf{1}[y^a_t > y^b_t](h^a_t(x^a_t - z) - g^b_t(x^b_t + z)) + \mathbf{1}[y^a_t \le y^b_t](-h^a_t(x^a_t + z) + g^b_t(x^b_t - z))$
    else
      $c^{a,b}_{t,2}(z) := \mathbf{1}[y^a_t > y^b_t](h^a_t(x^a_t - z) - h^b_t(x^b_t + z)) + \mathbf{1}[y^a_t \le y^b_t](-h^a_t(x^a_t + z) + h^b_t(x^b_t - z))$
    $\ell'_2 = \min\{z \mid c^{a,b}_{t,2}(z) = 0,\ z \in \mathbb{R}^+\}$ ▷ transfer capacity saturation point
    $v_2 = \int_0^{\min\{\ell,\ell'_2\}} c^{a,b}_{t,2}(z)\,\mathrm{d}z$ ▷ transmission value estimate
    $\underline{v}^{a,b}_t = \min\{v, v_2\}$
    $\bar{v}^{a,b}_t = \max\{v, v_2\}$
  if $y^a_t = cap^a$ **and** $y^b_t = cap^b$ **then** $\underline{v}^{a,b}_t = \bar{v}^{a,b}_t = 0$
return $\bar{v},\ \underline{v}$

Algorithm 1 Transmission value estimates accounting for market depth based on supply curve models. $\overline{v}$ contains the higher value estimates and $\underline{v}$ contains the lower value estimates. $\mathbf{1}[\cdot]$ is the indicator function that evaluates to 1 if the operand is true and 0 if the operand is false.

Algorithm 2 Screen supply curve models to identify those with a poor fit

Require: Parameters defining size of the acceptability buffer:
  Maximum acceptable absolute residual: Δ_1
  Maximum acceptable multiple of the median absolute deviation from the median: Δ_2
Require: Threshold for minimum proportion of points within acceptability buffer: Γ
  ▷ In this paper $\Delta_1 = \$25$, $\Delta_2 = 2$, and $\Gamma = 2/3$
Require: Non-decreasing supply curve models: $\{f_\tau^s\}_{s\in\text{PriceNodes},\tau=1,2,\ldots,(\#\text{ of periods})}$
Require: Data on net load and prices grouped by time period:
  $\{(X,Y)_\tau^s\} = \{\{(x_t^s, y_t^s)\}_{t=1,2,\ldots,\text{length of period }\tau}\}_{s\in\text{PriceNodes},\tau=1,2,\ldots,(\#\text{ of periods})}$
procedure SCREENMODELS($\{f_\tau^s\}$, $\{(X,Y)_\tau^s\}$, Δ_1, Δ_2, Γ)
  for $s \in$ PriceNodes **do**
    $T_s = \emptyset,\ P_s = \emptyset$
    for $\tau = 1, 2, \ldots, (\#\text{ of periods})$ **do**
      $\bar{y} = \text{Median}_{y\in Y_\tau^s}(y)$
      $mad = \text{Median}_{y\in Y_\tau^s}(|y - \bar{y}|)$
      if $\Gamma|X_\tau^s| \le \Sigma_{(x_t,y_t)\in(X,Y)_\tau^s}\mathbf{1}[\ |y_t - f_\tau^s(x_t)| \le \max\{\Delta_1,\ \Delta_2 \cdot mad\}\ ]$ **then**
        $P_s = P_s \cup \{\tau\}$
        $T_s = T_s \cup \{t \mid x_t^s \in X_\tau^s\}$
return $\{T_s\}_{s\in\text{PriceNodes}}$, $\{P_s\}_{s\in\text{PriceNodes}}$ ▷ hours and periods with a usable model

Algorithm 2 Screen supply curve models to identify those with a poor fit

Algorithm 3 Identify the steepest supply curves at high and low net load levels

Require: Non-decreasing supply curve models: $\{f_\tau^s\}_{s\in\text{PriceNodes},\tau=1,2,\ldots,(\#\text{ of periods})}$
Require: Net demand data partitioned by time period: $\{X_\tau^s\} = \{\{x_t^s\}_{t\in\tau}\}_{s\in\text{PriceNodes},\tau=1,2,\ldots,(\#\text{ of periods})}$
procedure STEEPESTSLOPE($\{f_\tau^s\}$, $\{X_\tau^s\}$)
  for $s \in$ PriceNodes **do**
    $\tau_+^s = \text{argmax}_{\tau=1,2,\ldots,(\#\text{ of periods})}\{f_\tau^{s\prime}(z) \mid z = \max\{x \mid x \in X_\tau^s\}\}$
    $x_+^s = \max\{x \mid x \in X_{\tau_+^s}^s\}$
    $\tau_-^s = \text{argmax}_{\tau=1,2,\ldots,(\#\text{ of periods})}\{f_\tau^{s\prime}(z) \mid z = \min\{x \mid x \in X_\tau^s\}\}$
    $x_-^s = \min\{x \mid x \in X_{\tau_-^s}^s\}$
return $\{\tau_+^s,\ x_+^s,\ \tau_-^s,\ x_-^s\}_{s\in\text{PriceNodes}}$

Algorithm 3 Identify the steepest supply curves at high and low net load levels

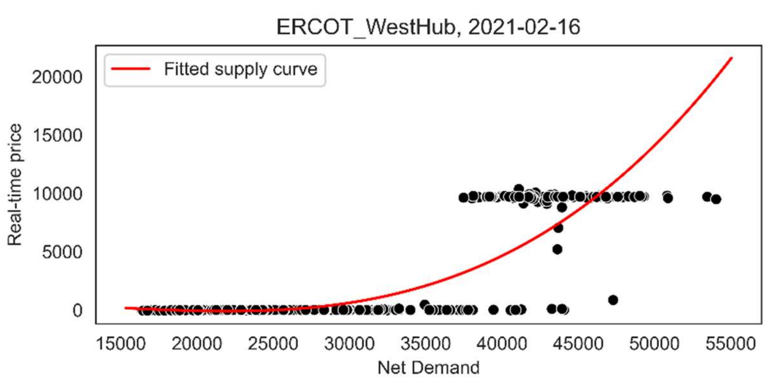

Figure 13 Example of supply curve model that fails to pass the screening process established in Algorithm 2. Each point represents an hour for ERCOT's West Hub during 2021-02-16 to 2021-02-28, a period that overlaps Winter Storm Uri.

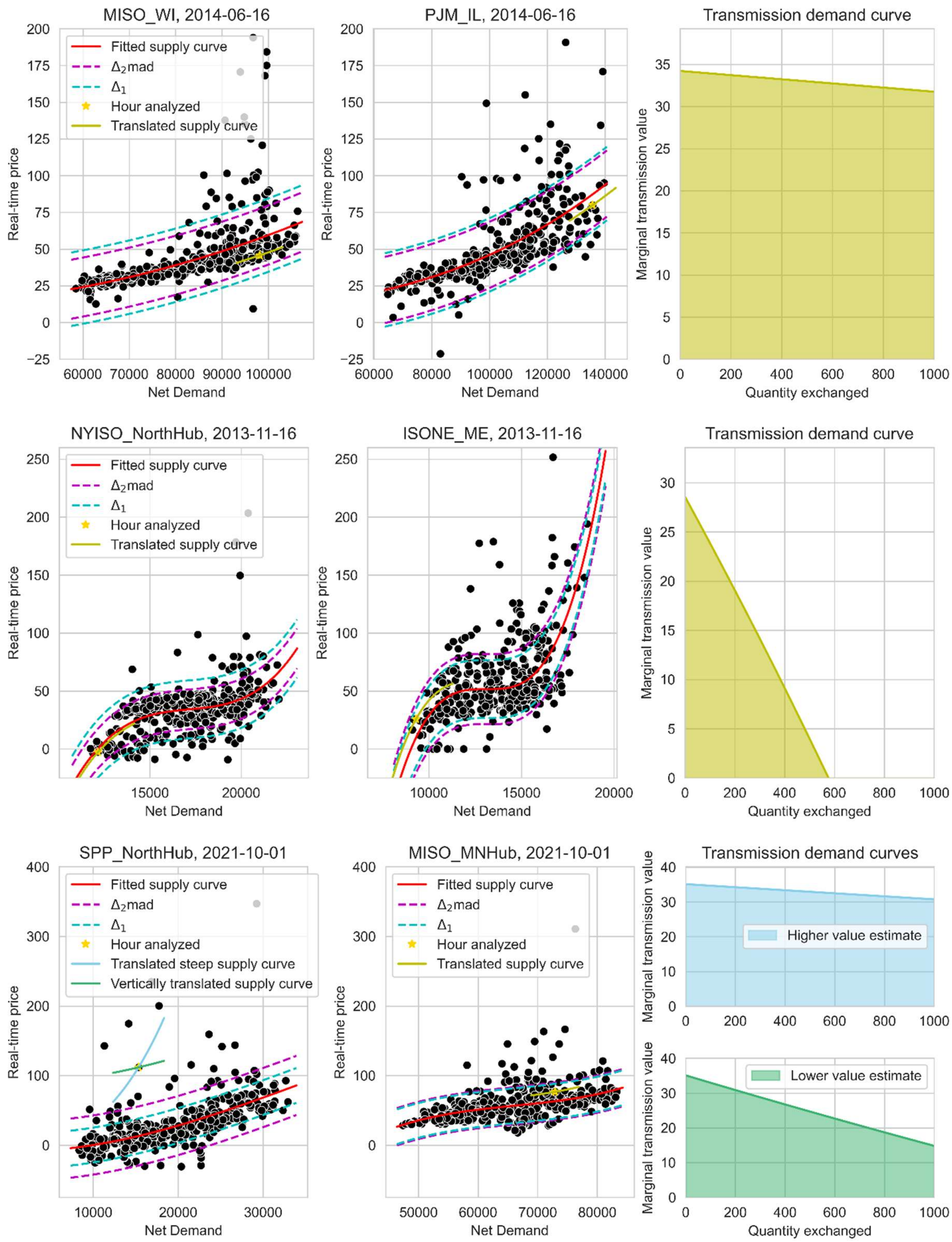

Figure 14 Examples of methodology for estimating transmission market value accounting for depth of a 1000 MW transmission capacity increase. Each black circle represents one hour within a bi-monthly period. (a) Example with limited saturation effects. (b) Example with significant saturation effects such that <600 MW of the additional 1000 MW capacity available is transferred. (c) Example one node with a residual greater than the tolerance (dashed lines), so two transmission value estimates are calculated. The estimates use the same translated supply curve to represent MISO_MNHub, but different curves to represent SPP_NorthHub.

Table 3 List of designated events used in the analysis, including NERC-identified periods of grid stress and key weather events identified in the literature.

Event Description	Start Date	End Date	#days	Sources
Cold	2/1/2011	2/4/2011	4	Novacheck (2021), NERC SOR (2012)
--	4/4/2011	4/4/2011	1	NERC SOR (2012)
Tornados, Severe Weather	4/27/2011	4/28/2011	2	NERC SOR (2012)
--	6/30/2011	6/30/2011	1	NERC SOR (2012)
--	7/1/2011	7/1/2011	1	NERC SOR (2012)
Heat	7/19/2011	7/24/2011	6	Novacheck (2021)
Hurricane	8/25/2011	8/30/2011	6	Novacheck (2021), NERC SOR (2012)
Southwest Blackout	9/8/2011	9/8/2011	1	NERC SOR (2012)
Severe Weather Northeast Snowstorm	10/29/2011	10/29/2011	1	NERC SOR (2012)
Severe Weather Tornadoes	3/2/2012	3/2/2012	1	NERC SOR (2013)
Severe Thunderstorm	5/29/2012	5/29/2012	1	NERC SOR (2013)
Heat (Novacheck), Thunderstorm Derecho (NERC SOR)	6/29/2012	7/7/2012	9	Novacheck (2021), NERC SOR (2013)
Severe Thunderstorm	7/18/2012	7/18/2012	1	NERC SOR (2013)
Severe Thunderstorm	7/24/2012	7/24/2012	1	NERC SOR (2013)
Hurricane Isaac	8/28/2012	8/29/2012	2	NERC SOR (2013)
Hurricane Sandy	10/29/2012	10/30/2012	2	NERC SOR (2013)
Equipment Failure	2/8/2013	2/8/2013	1	NERC SOR (2014)
Power System Condition, Fire	5/30/2013	5/30/2013	1	NERC SOR (2014)
Severe Thunderstorms	6/13/2013	6/13/2013	1	NERC SOR (2014)
Weather	6/23/2013	6/23/2013	1	NERC SOR (2014)
Severe Weather, Fault and Equipment Failure	6/26/2013	6/27/2013	2	NERC SOR (2014)
Rainfall Leading to Flooding, Severe Thunderstorms	7/8/2013	7/10/2013	3	NERC SOR (2014)
Heatwave	9/9/2013	9/11/2013	3	PJM (2013)
Severe Ice & Snow Storm	11/17/2013	11/17/2013	1	NERC SOR (2014)
Cold, Load Shed	12/4/2013	12/12/2013	9	Novacheck (2021), NERC SOR (2014)
Polar Vortex	1/3/2014	1/10/2014	8	Goggin (2021), NERC SOR (2015)
Winterstorm	1/21/2014	1/24/2014	4	NERC SOR (2015)
Winterstorm	1/29/2014	1/29/2014	1	NERC SOR (2015)
Thunderstorms	7/8/2014	7/8/2014	1	NERC SOR (2015)
Extreme Windstorm	12/11/2014	12/11/2014	1	NERC SOR (2015)
Severe Winter Weather	1/8/2015	1/8/2015	1	NERC SOR (2016)
Severe Winter Weather	2/20/2015	2/20/2015	1	NERC SOR (2016)
Severe Weather	6/23/2015	6/23/2015	1	NERC SOR (2016)
Severe Weather	6/30/2015	6/30/2015	1	NERC SOR (2016)
Severe Weather	7/13/2015	7/13/2015	1	NERC SOR (2016)
Severe Weather	7/18/2015	7/18/2015	1	NERC SOR (2016)
Thunderstorm/Showers	7/20/2015	7/20/2015	1	NERC SOR (2016)

Summer Weather	7/30/2015	7/30/2015	1	NERC SOR (2016)
Excessive Rainfall, Thunder/Lightning Storm	10/23/2015	10/23/2015	1	NERC SOR (2016)
Storm, Flooding, Straightline Winds	11/17/2015	11/17/2015	1	NERC SOR (2016)
--	6/27/2016	6/28/2016	2	NERC SOR (2017)
--	7/6/2016	7/6/2016	1	NERC SOR (2017)
--	7/8/2016	7/8/2016	1	NERC SOR (2017)
Severe weather	7/14/2016	7/14/2016	1	NERC SOR (2017)
--	7/21/2016	7/21/2016	1	NERC SOR (2017)
--	7/25/2016	7/25/2016	1	NERC SOR (2017)
Severe weather	8/11/2016	8/11/2016	1	NERC SOR (2017)
Severe weather	10/8/2016	10/8/2016	1	NERC SOR (2017)
--	10/24/2016	10/24/2016	1	NERC SOR (2017)
Winter storm	3/8/2017	3/8/2017	1	NERC SOR (2021)
Wind storm	4/7/2017	4/7/2017	1	NERC SOR (2021)
Unrelated coincidental generator outages	5/1/2017	5/1/2017	1	NERC SOR (2021)
Hurricane Irma	9/11/2017	9/11/2017	1	NERC SOR (2020)
Thomas Fire	12/4/2017	12/4/2017	1	NERC SOR (2021)
Thomas Fire	12/10/2017	12/10/2017	1	NERC SOR (2021)
Bomb Cyclone, Severe weather (load reduction), Severe weather (severe cold weather)	12/26/2017	1/19/2018	25	Goggin (2021), NERC SOR (2019)
Severe weather (winter NPCC, storm Riley)	3/2/2018	3/2/2018	1	NERC SOR (2019)
Severe weather (late season snow, storm)	4/15/2018	4/15/2018	1	NERC SOR (2019)
Severe weather (tornado, wind, hail)	5/15/2018	5/15/2018	1	NERC SOR (2019)
Natchez Fire	8/11/2018	8/11/2018	1	NERC SOR (2021)
Severe weather (hurricane Florence)	9/14/2018	9/14/2018	1	NERC SOR (2019)
Severe weather (tropical storm Michael)	10/11/2018	10/11/2018	1	NERC SOR (2019)
Severe weather (winter storm Avery)	11/15/2018	11/15/2018	1	NERC SOR (2019)
Winter Storm Indra	1/21/2019	1/21/2019	1	NERC SOR (2020)
Polar vortex 31idwest, Winter Storm Jayden	1/30/2019	2/1/2019	3	Goggin (2021), NERC SOR (2020)
Winter Storms Maya and Nadya	2/12/2019	2/12/2019	1	NERC SOR (2020)
Wind Storm, Winter Storms Quiana and Ryan	2/24/2019	2/25/2019	2	NERC SOR (2020)
Coincidental Generator Outages	7/22/2019	7/22/2019	1	NERC SOR (2020)
Heat	8/5/2019	8/16/2019	12	Goggin (2021)
Coincidental Generator Outages	9/3/2019	9/3/2019	1	NERC SOR (2020)
Saddleridge Fire	10/11/2019	10/11/2019	1	NERC SOR (2020)
Coincidental Generator Outages	11/27/2019	11/27/2019	1	NERC SOR (2020)
Arctic outbreak + extreme cold + thunderstorms	1/11/2020	1/11/2020	1	NERC SOR (2021)
Arctic outbreak + extreme cold + “Nor’easter”	1/12/2020	1/12/2020	1	NERC SOR (2021)
Easter Tornado	4/13/2020	4/13/2020	1	NERC SOR (2021)
Tropical Storm Amanda: Cristobal	6/3/2020	6/3/2020	1	NERC SOR (2021)
Tropical Storm Amanda: Cristobal	6/9/2020	6/9/2020	1	NERC SOR (2021)

Unrelated coincidental generator outages	7/1/2020	7/1/2020	1	NERC SOR (2021)
Hurricane Isaias	8/4/2020	8/4/2020	1	NERC SOR (2021)
Windstorms	8/10/2020	8/10/2020	1	NERC SOR (2021)
CA/West heat, Extreme heat and demand with load shed-California	8/14/2020	8/19/2020	6	Goggin (2021), NERC SOR (2021)
Hurricane Laura	8/27/2020	8/27/2020	1	NERC SOR (2021)
Johnson Fire	8/28/2020	8/28/2020	1	NERC SOR (2021)
Wild fires	9/7/2020	9/8/2020	2	NERC SOR (2021)
Ice storm + Hurricane Zeta	10/28/2020	10/28/2020	1	NERC SOR (2021)
Hurricane Zeta	10/29/2020	10/29/2020	1	NERC SOR (2021)
High winds	11/15/2020	11/15/2020	1	NERC SOR (2021)
Texas cold	2/12/2021	2/20/2021	9	Goggin (2021), NERC SOR (2022)
Major thunderstorms	6/21/2021	6/21/2021	1	NERC SOR (2022)
Heatwave, Heat Dome and major thunderstorms	6/26/2021	6/28/2021	3	NERC SOR (2022)
Hurricane Nicholas and special protection system misoperation dropping generation	9/13/2021	9/13/2021	1	NERC SOR (2022)
December windstorm and tornadoes	12/11/2021	12/11/2021	1	NERC SOR (2022)
Winter Storm Elliott	12/22/2022	12/25/2022	4	Goggin and Zimmerman (2023), Energy Ventures Analysis (2023), NOAA (2024)
Hurricane Ian	9/28/2022	9/30/2022	3	NOAA (2024)
Hurricane Nicole	11/10/2022	11/11/2022	2	NOAA (2024)
Southern Tornado Outbreak	3/30/2022	3/30/2022	1	NOAA (2024)
Southeastern Tornado Outbreak	4/4/2022	4/6/2022	3	NOAA (2024)
Kentucky and Missouri Flooding	7/26/2022	7/28/2022	3	NOAA (2024)
Central Derecho	6/13/2022	6/13/2022	1	NOAA (2024)
Southern and Central Severe Weather	5/1/2022	5/3/2022	3	NOAA (2024)
Southern Severe Weather	4/11/2022	4/13/2022	3	NOAA (2024)
Central Severe Weather	6/7/2022	6/8/2022	2	NOAA (2024)
North Central Severe Weather	5/11/2022	5/12/2022	2	NOAA (2024)
North Central and Eastern Severe Weather	7/22/2022	7/24/2022	3	NOAA (2024)
Texas Hail Storms	2/21/2022	2/22/2022	2	NOAA (2024)
North Central Hail Storms	5/9/2022	5/9/2022	1	NOAA (2024)
North Central Hail Storms	5/19/2022	5/19/2022	1	NOAA (2024)

References for Table 3

- Energy Ventures Analysis. (2023) “Operation of the U.S. Power Generation Fleet During Winter Storm Elliott,” https://www.evainc.com/wp-content/uploads/2023/02/2023_02_23-EVA-Winter-Storm-Elliott-Report.pdf
- Goggin M. and Zimmerman Z., (2023) “The Value of Transmission During Winter Storm Elliott,” Grid Strategies. https://acore.org/resources/the-value-of-transmission-during-winter-storm-elliott
- Goggin M. (2021) “Transmission Makes the Power System Resilient to Extreme Weather,” Grid Strategies. https://acore.org/transmission-makes-the-power-system-resilient-to-extreme-weather

- NERC SOR (2022). "2022 State of Reliability, An Assessment of 2021 Bulk Power System Performance." North American Electric Reliability Corporation. Reports for years 2012 – 2022 available at: https://www.nerc.com/pa/RAPA/PA/Pages/default.aspx
- NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2024). https://www.ncei.noaa.gov/access/billions/, DOI: 10.25921/stkw-7w73
- Novacheck et al. (2021) "The Evolving Role of Extreme Weather Events in the US Power System with High Levels of Variable Renewable Energy" National Renewable Energy Lab. (NREL), NREL/TP-6A20-78394. https://doi.org/10.2172/1837959
- PJM Interconnection (2013) "Technical Analysis of Operational Events and Market Impacts During the September 2013 Heat Wave." https://hepg.hks.harvard.edu/sites/hwpi.harvard.edu/files/hepg/files/20131223-technical-analysis-of-operational-events-and-market-impacts-during-the-september-2013-heat-wave.pdf?m=1523366870