Simplified Market Mechanisms for Non-Convex Markets: Evidence from Italian Electricity Market

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Motivation

- Non-convexities present in many markets: telecommunications, airlines, railroads, postal delivery, retailing, ..., and electricity
  - Fixed costs to operate
  - Common costs across products
  - Minimum feasible output levels
  - Discrete feasible output levels
- How to organize these markets to achieve efficient outcomes is a generally unsolved problem in economics [Starr, 1969, Guesnerie, 1975]

Motivation (cont'd)

Non-convexities in air travel vs. electricity

Air Travel

- Only few people on flight from A to B
- Fixed costs of operating flight not covered
- Anecdotal evidence: Operator may claim "technical issues" and cancels flight
- Consequence: Passengers unhappy, but booked on later flight

Electricity

- Power plant owner finds out that at given (uncertain) market price for next day would prefer not to produce
- Fixed costs of operating power plant not covered
- If power plant was to decide to not produce this causes a *system-wide risk*, i.e., lights could go out for state/country/region

MOTIVATION (CONT'D)

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MOTIVATION (CONT'D)

Market efficiency and system reliability consequences

- Non-convexities at the individual level (can create incentivizes for unit owner not to produce)
- Non-convexities at the system level (can make it impossible to find replacement)
- In real-time; (i) locational demand must equal locational supply plus net imports at thousands of locations *and* (ii) this electricity must be within certain quality bands (frequency, voltage)

All US regions and Europe operate a day-ahead market that sets market-clearing prices and quantities for the next day, and kicks off (market based) real-time system operation

- Approaches in US and Europe differ in terms of extent to which all real-time physical system operating constraints are reflected in day-ahead market mechanism[1]

[1] Imran and Kockar [2014] provide a technical comparison on wholesale markets design in North America and Europe. See also Wilson [2002], Pollitt and Anaya [2016], De Vries and Verzijlbergh [2018], Newbery et al. [2018], Newbery [2018], Ahlqvist et al. [2019], Joskow [2019], Wolak [2021] for different perspectives on the question of how to organize wholesale electricity markets.

TWO SOLUTIONS TO NON-CONVEXITIES

Early (Zonal) US market design and current European market design

- Day-ahead market with *simplified* network model that ignores start-up costs, and minimum safe operating levels
- Assumes infinite transmission capacity between locations within region or within zones in region
- Before real-time, re-dispatch process is required to ensure a secure operation of the grid respecting all real-time transmission and generation unit operating constraints

Two Solutions to Non-Convexities (Cont'd)

Current (Nodal) US market design

- Day-ahead market models *all* relevant transmission network constraints, and generation unit operating constraints (allows co-optimization of energy and ancillary services, e.g., reserves)
- Does *not* allow schedules from generation units to emerge from day-ahead market that would violate secure real-time grid operation
- Real-time market operates in same manner as day-ahead market but with real-time locational demands and output from renewables

What is the cost of a simplified market design?

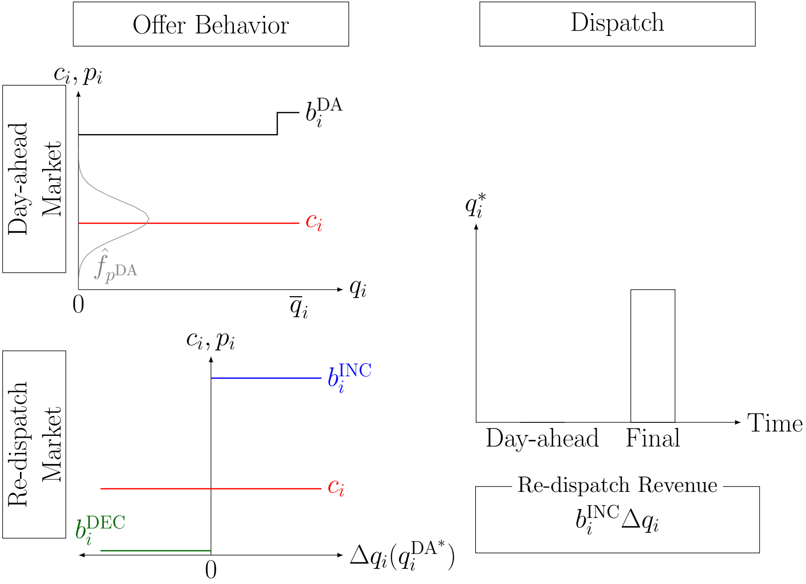
Simplified (zonal) day-ahead financial market with pay-as bid re-dispatch process more expensive than day-ahead locational marginal pricing (LMP) market that only allows generation schedules in day-ahead that are compatible with real-time operation

RESEARCH QUESTIONS

1. Analyze opportunities for suppliers in a *simplified* market mechanism to profit from the difference between the model used to operate the electricity market and how the grid is actually operated ("INC/DEC-Game")[2]
   - INC-Game: underselling of resources in the day-ahead market that are likely to be needed in real-time
   - DEC-Game: overselling of resources in the day-ahead market that are likely to be *not* needed in real-time
2. What is the cost of simplified market relative to integrated US-style market?
   - Counterfactual US-style market design where suppliers submit offer prices that are 140 percent of their marginal costs during peak hours of day yields similar average wholesale energy costs to consumers as the existing simplified market design

[2] Hirth and Schlecht [2019] provide some descriptive statistics on the situation in Germany. Recently, Sarfati et al. [2019], Sarfati and Holmberg [2020] developed mathematical models aiming to simulate and evaluate zonal electricity market designs and their performance.

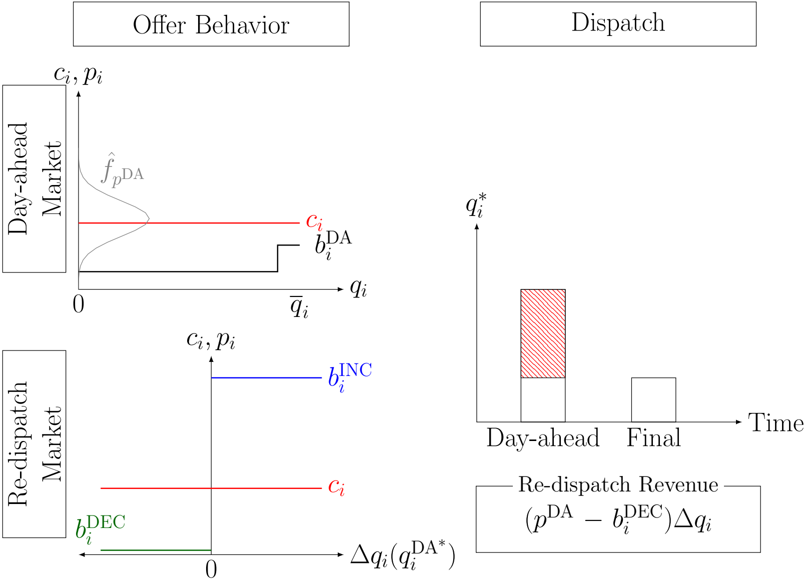
INC BIDDING STRATEGY



Re-dispatch Revenue

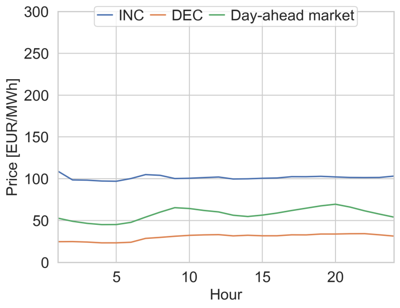
$b_i^{\mathrm{INC}} \Delta q_i$

DEC BIDDING STRATEGY

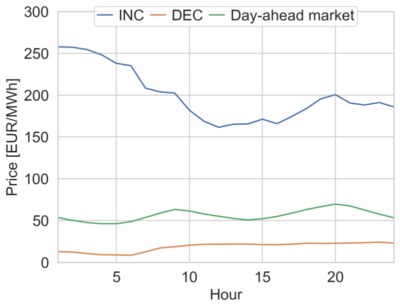


Incentives to Buy/Sell in Re-Dispatch Market

North Bidding Zone



Center-South Bidding Zone



Key Takeaway

Price[1] received [paid] for INCremental [DECremental] energy above [below] the day-ahead market price

[1] Real-time re-dispatch market pays as-bid and the prices in the figure represent the hourly median accepted price bids. Daily averages for 2017–2018.

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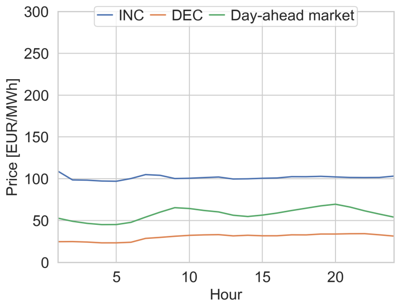

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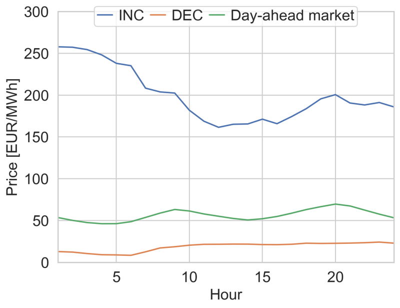

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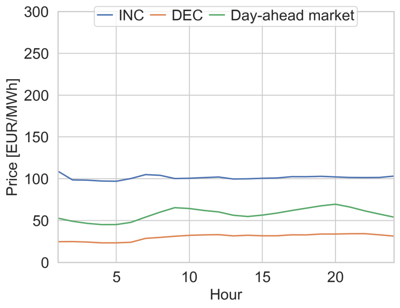

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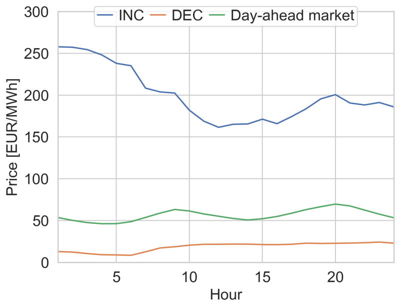

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RECAP

- A rich set of constraints (e.g., transmission, voltage, frequency, reserves) necessary for a *secure* real-time operation of the grid. These are not accounted for in the day-ahead market model
- Market participants are aware of these constraints and face a potentially large incentive to earn higher price from INC in re-dispatch market or buy back energy sold at day-ahead market-clearing price at offer price as a DEC in re-dispatch market
- Market participants must be able to *predict* if and when these constraints will be binding in order to from profit INCs and DECs in re-dispatch market

Empirical Analysis—Step 1

Estimate generation unit-level models of hourly probability of INC or DEC in re-dispatch market

Sample selection

- Use hourly unit-level offer curves for the day-ahead market and real-time re-dispatch market between 2017 and 2018
- Select most important combined cycle gas turbine units (provided by Terna) that are used to for re-dispatching

EMPIRICAL ANALYSIS—STEP 1 (CONT'D)

Prediction models

- Machine learn (random forest model)[3] probability that a unit will be INCed/DECed using forecasts of system conditions known before the day-ahead market closes
  - National zonal day-ahead forecasts for demand and renewables
  - Neighboring countries' (+ Germany) day-ahead forecasts for demand and renewables
  - Day-ahead market cross-border transmission limits with adjacent countries and the national zonal transmission limits
  - Month-of-year, hour-of-day, and workday indicator variables

▸ Model details

[3] Results also hold when machine-learning models are replaced by binary logit model

Empirical Analysis—Step 2

Calculating day-ahead offer markups

- Defined as the day-ahead market offer-price minus short-run marginal cost estimate
- Unit-level short-run marginal cost estimates are based on heat-rates estimates, fuel-cost, environmental cost such as CO_2 emissions allowances, and variable operations and maintenance cost
- We use the offer-quantity weighted average offer-price to have a single day-ahead market offer price number for each unit and hour

Key Takeaway

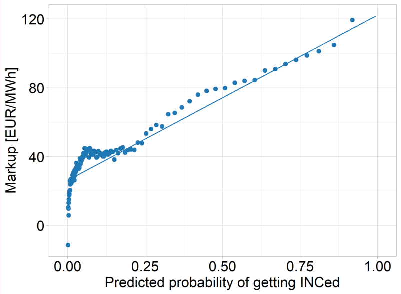
For each unit and hour of the sample we obtained a day-ahead market offer markup and a predicted probability of getting INCed or DECed in the real-time re-dispatch market

Graphical Results

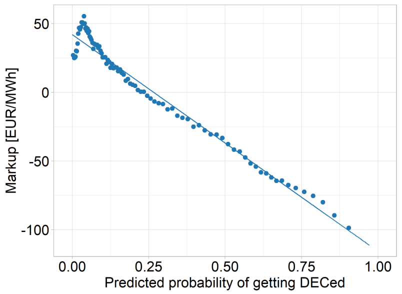
Binscatter [Cattaneo et al., 2019] of unit-level day-ahead offer markup and unit-level estimated probability of getting INCed/DECed

Note: Control for unit, hour-of-day, day-of-week, month-of-year fixed effects using Cattaneo et al. [2019] nonparametric approach. Number of bins minimizes the (asymptotic) integrated mean squared error.

INC ($N = 612,939$)



DEC ($N = 497,148$)



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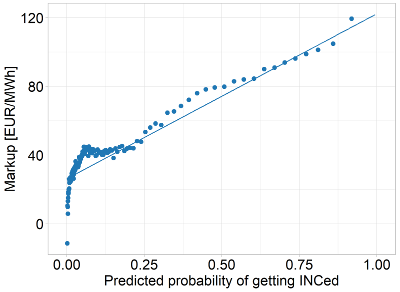

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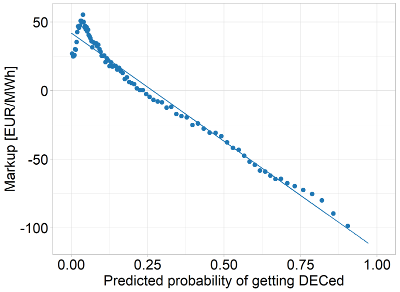

INC Regression Results

	INC			
	(1)	(2)	(3)	(4)
Predicted $\mathbb{P}_i[y_i = 1 \mid X]$	80.50 (20.93)	89.08 (16.39)	79.14 (14.34)	104.61 (17.48)
Net Load				10.86 (2.25)
$(\text{Net Load})^2$				−0.44 (0.08)
$(\text{Net Load})^3$				0.00 (0.00)
Unit FEs	X	X	X	X
Hour-of-day FEs		X	X	X
Day-of-week FEs				X
Month-of-year FEs		X	X	X
Unit × Month FEs			X	
N	612,939	612,939	612,939	612,939

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Net load is the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.

Average day-ahead market price: 57.7 EUR/MWh

Average (std dev) predicted probability of getting INCed: 0.14 (0.19)

Key Takeaway

Average day-ahead offer markup increases by about 8 EUR/MWh if the predicted probability of getting INCed increases by 0.1

DEC Regression Results

	DEC			
	(1)	(2)	(3)	(4)
Predicted $\mathbb{P}_i[y_i = 1\|X]$	−158.69 (31.79)	−156.88 (30.31)	−146.93 (29.84)	−157.86 (28.50)
Net Load				−1.05 (2.23)
(Net Load)^2				−0.02 (0.07)
(Net Load)^3				−0.00 (0.00)
Unit FEs	X	X	X	X
Hour-of-day FEs		X	X	X
Day-of-week FEs				X
Month-of-year FEs		X	X	X
Unit × Month FEs			X	
N	497,148	497,148	497,148	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Net load is the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.

Average day-ahead market price: 57.7 EUR/MWh

Average (std dev) predicted probability of getting DECed: 0.25 (0.25)

Key Takeaway

Average day-ahead offer markup decreases by about 15 EUR/MWh if the predicted probability of getting DECed increases by 0.1

Double/Debiased Machine Learning

- Replace small set of control variables in the previous regressions by a rich set of control variables: Zonal residual demands (national and neighbouring countries + Germany), squared terms and interaction terms thereof; transmission limits; gas prices, gas prices squared and interaction of gas prices with zonal residual demands; unit, hour, workday, and month fixed effects
- Naïve approach: Estimate model using LASSO
  - Resulting estimates are biased due to the L1-regularization term introduced in LASSO
- Solution: "Double/debiased machine learning for treatment and structure parameters," Chernozhukov et al. [2018]

	INC	DEC
Predicted $\mathbb{P}_i[y_i = 1 \mid X]$	87.40 (8.47)	−128.83 (8.26)
N	612,939	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Standard errors (clustered at the unit level) in parentheses.

ROBUSTNESS

Replace machine learned unit-level predictions of getting INCed/DECed by standard logistic regression model predictions	✔
Enhanced unit-level prediction models accounting e.g., portfolio effects	✔
Include all CCGTs	✔
Rational expectation assumption; Instrument observed re-dispatch occurrences with predicted re-dispatch likelihood	✔
Restrict sample to relevant market transactions	✔
Replace day-ahead offer mark-up by "competitively offered quantity"	✔

MOST CONSERVATIVE ESTIMATES

Average day-ahead offer markup increases [decreases] by about 5 EUR/MWh [6 EUR/MWh] if the predicted probability of getting INCed [DECed] increases by 0.1

Counterfactual Analysis

Task: Compare actual total costs to serve load to the costs that *would* originate in a US-style market assuming different levels of uniform markups

- Compare actual market outcomes to a non-convex market clearing mechanism that accounts for all relevant system constraints and non-convexities (US-style market)[4]
- Find level of uniform markups on marginal costs that leads to the same amount of total costs as current costs
- $P^{\text{Actual}}Q \approx P^{\text{Markup}}Q$
- Incentive to pursue INC/DEC strategies largely eliminated in current US market design
  - DECs eliminated because all relevant operating constraints are respected in the day-ahead market
  - INCs addressed through the automatic local market power mitigation mechanisms that exist in US markets [see, e.g., Graf et al., 2021, for an overview]

[4] See Graf et al. [2020] on how to derive a competitive benchmark explicitly accounting for non-convexities and demand for system services

COUNTERFACTUAL ANALYSIS (CONT'D)

	Actual	Competitive	10% Markup		15% Markup		40% Markup	
			6:00–22:00	16:00–22:00	6:00–22:00	16:00–22:00	6:00–22:00	16:00–22:00
Day-ahead Market Costs [EUR/MWh Demand]	62.6	–	–	–	–	–	–	–
Intraday Market/Re-dispatch Costs [EUR/MWh Demand]	6.7	–	–	–	–	–	–	–
Energy Costs [EUR/MWh Demand]	–	63.6	67.2	65.0	69.0	65.7	78.0	69.2
Make-whole payments [EUR/MWh Demand]	–	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Total Cost [EUR/MWh Demand]	69.2	64.0	67.6	65.4	69.4	66.1	78.4	69.6
Savings [EUR/MWh Demand]		5.2	1.6	3.8	−0.2	3.1	−9.2	−0.4
Annual Savings, 300 TWh demand [Billion EUR]		1.6	0.5	1.2	−0.1	0.9	−2.7	−0.1

Counterfactual Analysis (Cont'd)

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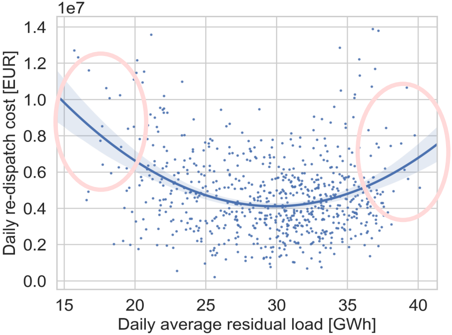
Simplified Market Mechanisms and Renewables



Residual load or residual demand:

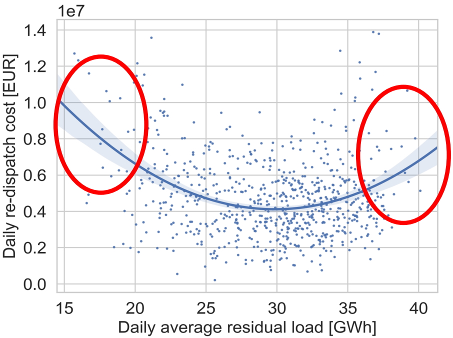
Demand net of renewables

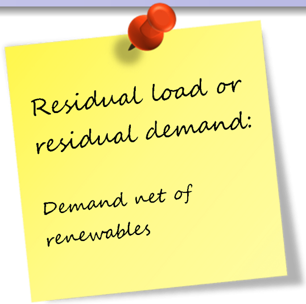
Key Takeaways

- U-shaped relation between re-dispatch cost and residual load
- System operator has typically a lot of options to re-dispatch on an "average day" but less so on extreme days
- *Economic* re-dispatch costs approximately 15% percent of the total cost of wholesale energy valued at the day-ahead price

Re-dispatch cost computation   Additional content

Simplified Market Mechanisms and Renewables





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Re-dispatch cost computation | Additional content

CONCLUSION

- Simplified market mechanism incentivizes market participants to offer at high [low] price in day-ahead market if it is expected to be INCed [DECed] and paid as-bid or as-offered in re-dispatch process
- Counterfactual analysis reveals that if market participants added markup uniformly over all dispatchable units of 40% during peak residual demand hours leads to approximately the same average total costs to serve demand under an US-style market design
- U-shaped relationship between re-dispatch costs and net demand (system demand less renewables production)
  - Both, low levels of net demand and high levels of net demand reduce options for system operator to maintain a reliable grid
  - Re-dispatching volumes are likely to increase when scaling up renewable capacity (without grid investments, flexible technologies, and demand side participation)
- Policy implications: Many regions, e.g., Germany, UK, Australia are re-thinking their simplified market designs

THANK YOU FOR YOUR ATTENTION!

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Simplified Market Mechanisms and Renewables

- Existing transmission infrastructure largely planned and build *in conjunction* with conventional generation
- Renewables reduce capacity factors of conventional plants: lower emissions; crowding-out (retirement) of conventional generation
- (On average) lower and more volatile residual demand can increases number of start-ups, ramping requirements, hours operating at minimum load level for conventional units
- Renewables (especially decentralized solar) enter the system un-coordinated with the existing transmission infrastructure

Potential Operational Consequences

- Frequency/magnitude of congestion in the grid likely to increase
- Demand for system security services likely to increase
- Re-dispatching volumes are likely to increase without investments in the grid capacity and flexible technologies

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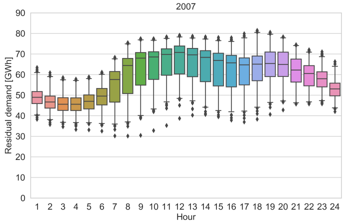
Renewables and Residual Demand Variability

Where and when renewables deployment has increased, primarily in the form of wind and solar energy,

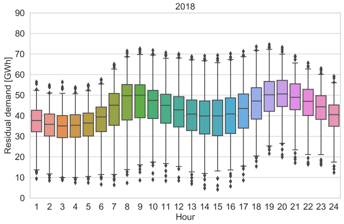
- Variability in Residual demand, system demand less renewables production, has significantly increased

The Case of Germany (*Energiewende*)

2007



2018



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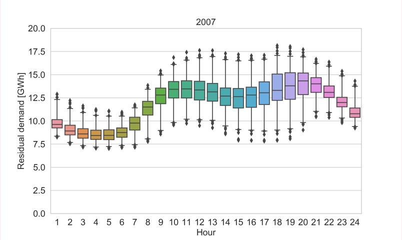
Italy (Area South of Tuscany)

2007



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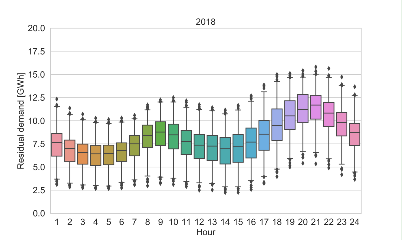

- Most Renewable capacity installed in the southern part of Italy
- On top of that also a lower demand level due to the lasting effects of 2008 economic crisis

Key Takeaway

Temporal and spatial residual demand distributions very different today then a decade ago

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CONSEQUENCES (SYSTEM-WIDE)

INTENDED CONSEQUENCE

Significant reduction in CO_2 emissions but also local pollutants

Increased relevance of system operating constraints

- Increased demand for ramping energy (“duck-curve”)
  - More flexible capacity needs to be on-line
- Low residual demand levels
  - More units in “must-run” or "minimum load" status
- Increased residual demand uncertainty
  - More reserve requirements
- Transmission constraints may bind more frequently
  - Locational supply “curtailment”
- Security constraints, e.g., voltage, may bind more frequently
  - Demand for *specific* units across the network

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CONSEQUENCES (UNIT-LEVEL)

- For some units, increased risk of being turned on or dispatched up relative to their day-ahead schedule after day-ahead market-clearing
- For some units, increased risk of not being dispatched or have their day-ahead schedule reduced after day-ahead market-clearing
- Increased risk of large imbalance payments if a day-ahead market schedule is not physically feasible
- Start-up cost and ramping-cost become more important factors
  - Day-ahead market does not guarantee start-up and minimum load cost recovery, but re-dispatch market does
- Lower capacity factors

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EU-Wide Firmness Costs

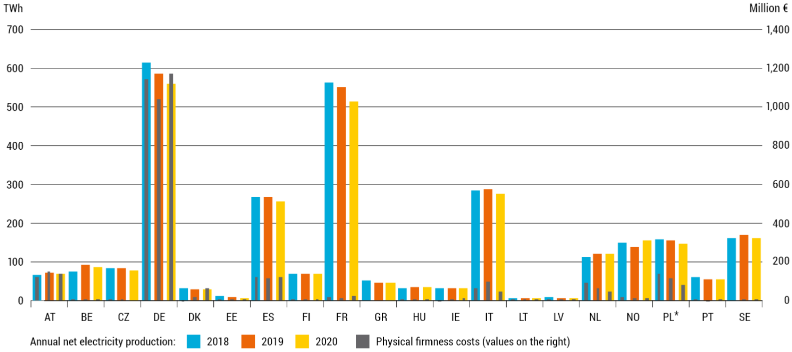

Figure 118. Total amount of physical firmness costs [millions of euro] (sum of figures presented in Figures 64 and 65) and annual net electricity production [TWh]. *Since PSE applies ISP, the cost and volume reported by PSE cover the whole ISP, i. e., not only congestion management, and thus reported cost and volume should be deemed to be strongly overestimated. For a more detailed explanation, see Section 4.2.2.1.

Notes: These costs represent only intra-zonal congestion costs. In case of Italy that is only as small fraction (about 10%) of the total re-dispatching costs. Source: ENTSO-E Bidding Zone Configuration, Technical Report 2021.

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MODEL DETAILS

We code y to be equal to one if a unit's schedule is INCed [DECed] and zero otherwise. We separately estimate the parameter vector β for each unit and for each re-dispatch market product, i.e., for INC and DEC energy separately, imposing a model of the form

$$\mathbb{P}[y = 1|X] = F(X\beta) \tag{1}$$

- $F(t)$ in (1) can be replaced by logistic cumulative distribution function and the model becomes standard logit model
- Estimate β using cross-validated random forest classification model

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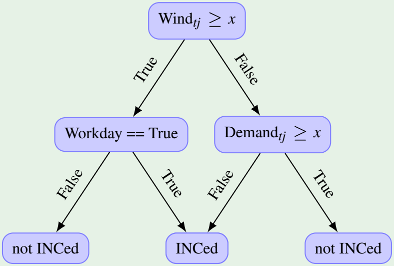
Random Forest Model—Intuition

Will a specific unit located in zone j at time t get INCed?

Sample Decision Tree



Random Forest

- Random forest is collection or random decision trees
- Each decision tree in forest produces class prediction and the mode of all the classes becomes the model's prediction (Majority-voting)
- Cross-validation strategy using 20% of the sample as test data and the remainder as training data to prevent *over-fitting*

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Forecast Models—Performance Metrics

Define

$$\hat{y} = \begin{cases} 1, & \text{if predicted } P[y = 1|X] > 0.5 \\ 0, & \text{otherwise} \end{cases}$$

for each unit, time, and product (INC, DEC).

- "Accuracy" metric measures how often the classifier is correct, i.e., summing up the true positives and the true negatives and dividing by the sample size.
- "Precision" metric is how often the positive predicted values are correct, i.e., the number of true positives divided by the sum of the number of true positives and the number of false positives
- "Recall" or "Sensitivity" metric is the true positive rate, i.e., the number of correctly identified positives divided by the total number of actual positives

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Forecast Models—Performance

Mean and standard deviation of unit-level metrices across all units

	INC		DEC	
	(1)	(2)	(3)	(4)
Accuracy	0.89	0.94	0.82	0.89
	(0.06)	(0.03)	(0.07)	(0.03)
Precision	0.68	0.98	0.66	0.93
	(0.08)	(0.03)	(0.07)	(0.07)
Recall	0.29	0.50	0.38	0.53
	(0.18)	(0.17)	(0.23)	(0.25)

- Columns (1) and (3) correspond to the logit model
- Columns (2) and (4) correspond to the cross-validated random forest model
- Random forest model outperforms the logit model across all measures for INC as well as for DEC (our preferred model)

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Re-Dispatch Cost Computation

- Actual hourly real-time re-dispatch cost:
  $\sum_j p_j^{\text{INC}} q_j^{\text{INC}} - p_j^{\text{DEC}} q_j^{\text{DEC}}$
- Does not contain the economic value of energy sold in the day-ahead market that is useless in real-time
- Economic hourly real-time re-dispatch cost:
  $\sum_j (p^{\text{DA}} - p_j^{\text{DEC}}) q_j^{\text{DEC}} + p_j^{\text{INC}} q_j^{\text{INC}}$

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