Forecasting in blockchain-based smart grids

The art of smart energy trading

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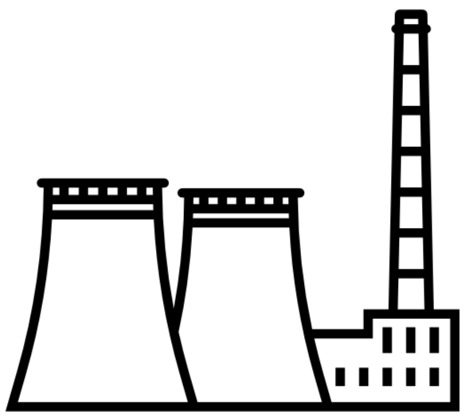
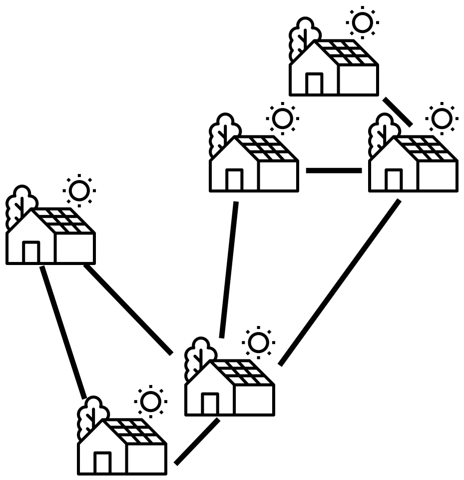
Content

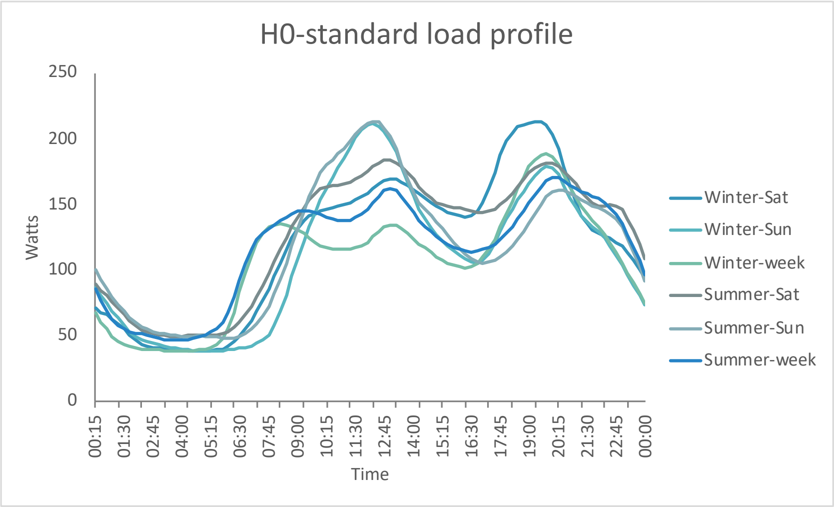
Challenge	Transformation of energy landscape
Solution	Local energy markets
Functioning	Market mechanism as smart contract
Prerequisite	Accurate forecasts
Study	Forecast evaluation and market outcomes
Conclusion	Better forecasts or different market mechanism

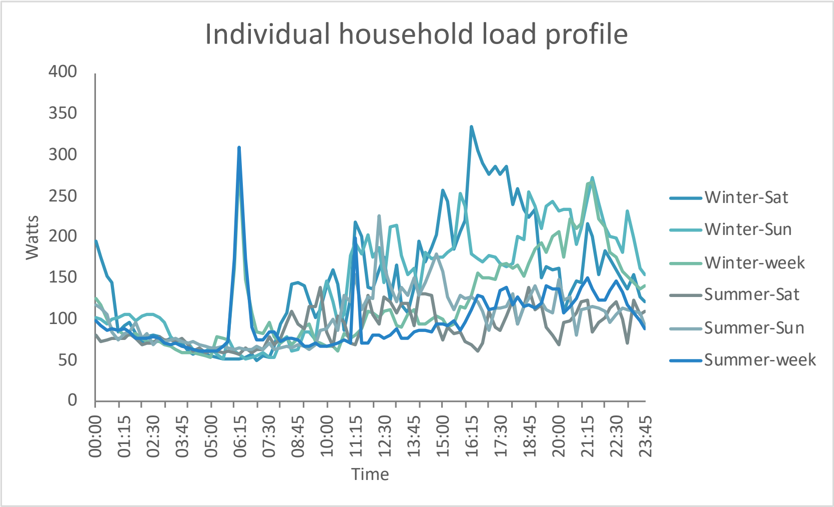
Transformation of energy landscape

From this… … to this









Data source: Zörner, T. (2013), Blog.Stromhaltig. URL: https://blog.stromhaltig.de/2013/01/wir-bauen-uns-ein-lastprofil/#jumper [accessed on: 12.11.2018].

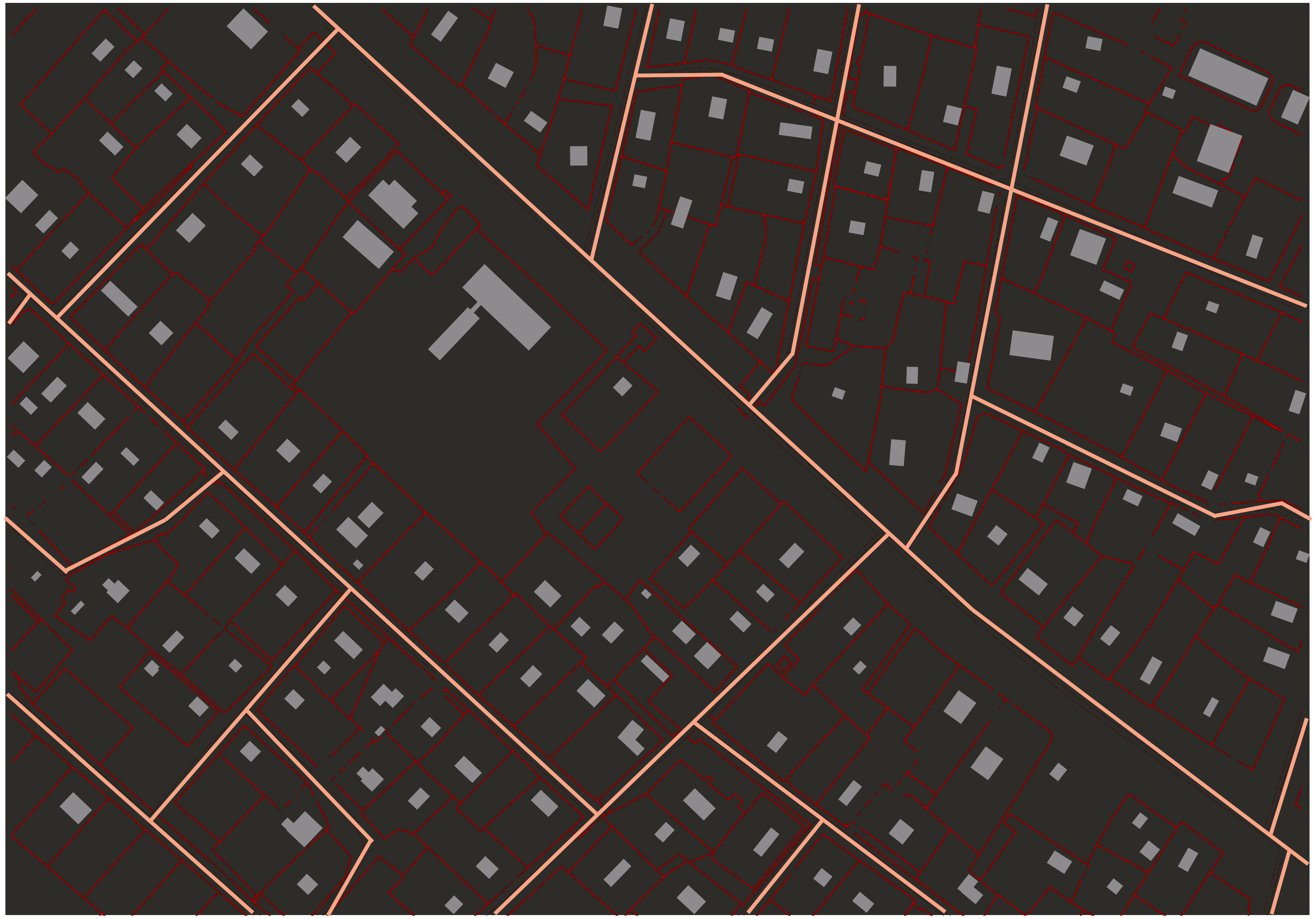
Transformation of energy landscape

- Transformation of energy landscape
  - More renewable energy generators
  - More distributed production
  - More feed-in in low voltage grids

- Problems
  - Increasing difficulty to manage grid load
  - Suboptimal utilization of renewable energy resources
  - Dependency on central energy suppliers

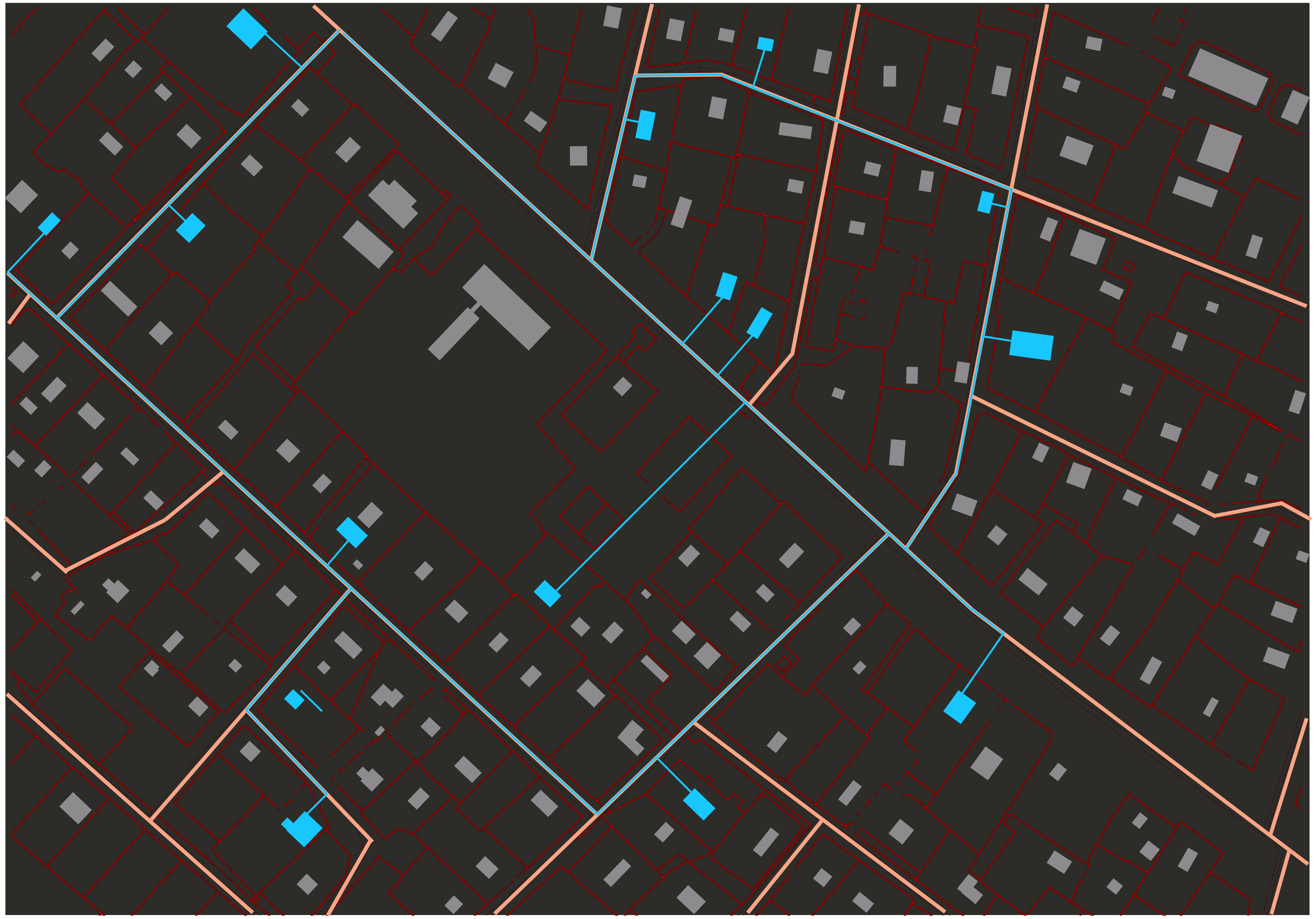
Local energy markets

In a neighbourhood …



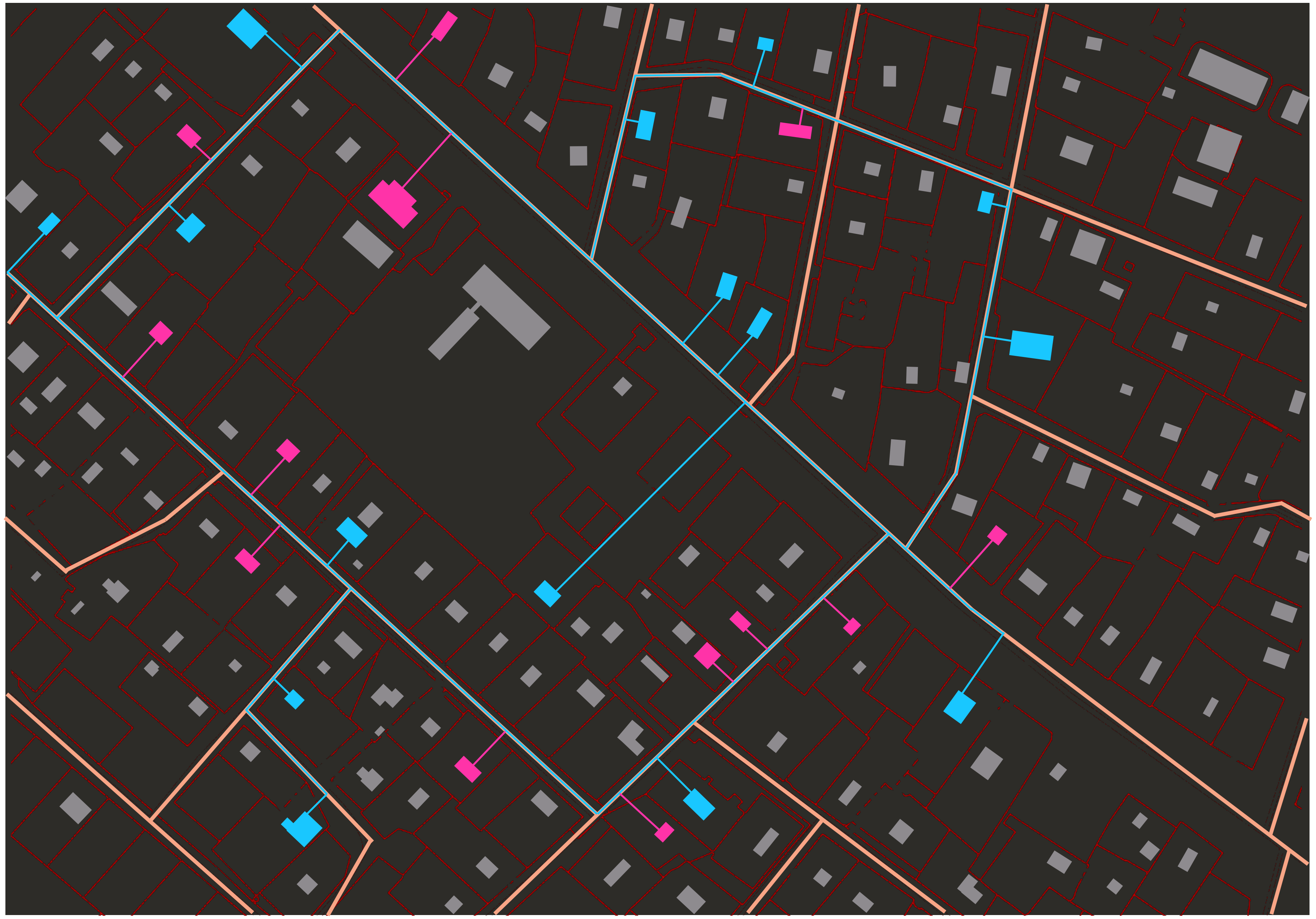
Local energy markets

… producers of renewable energy…



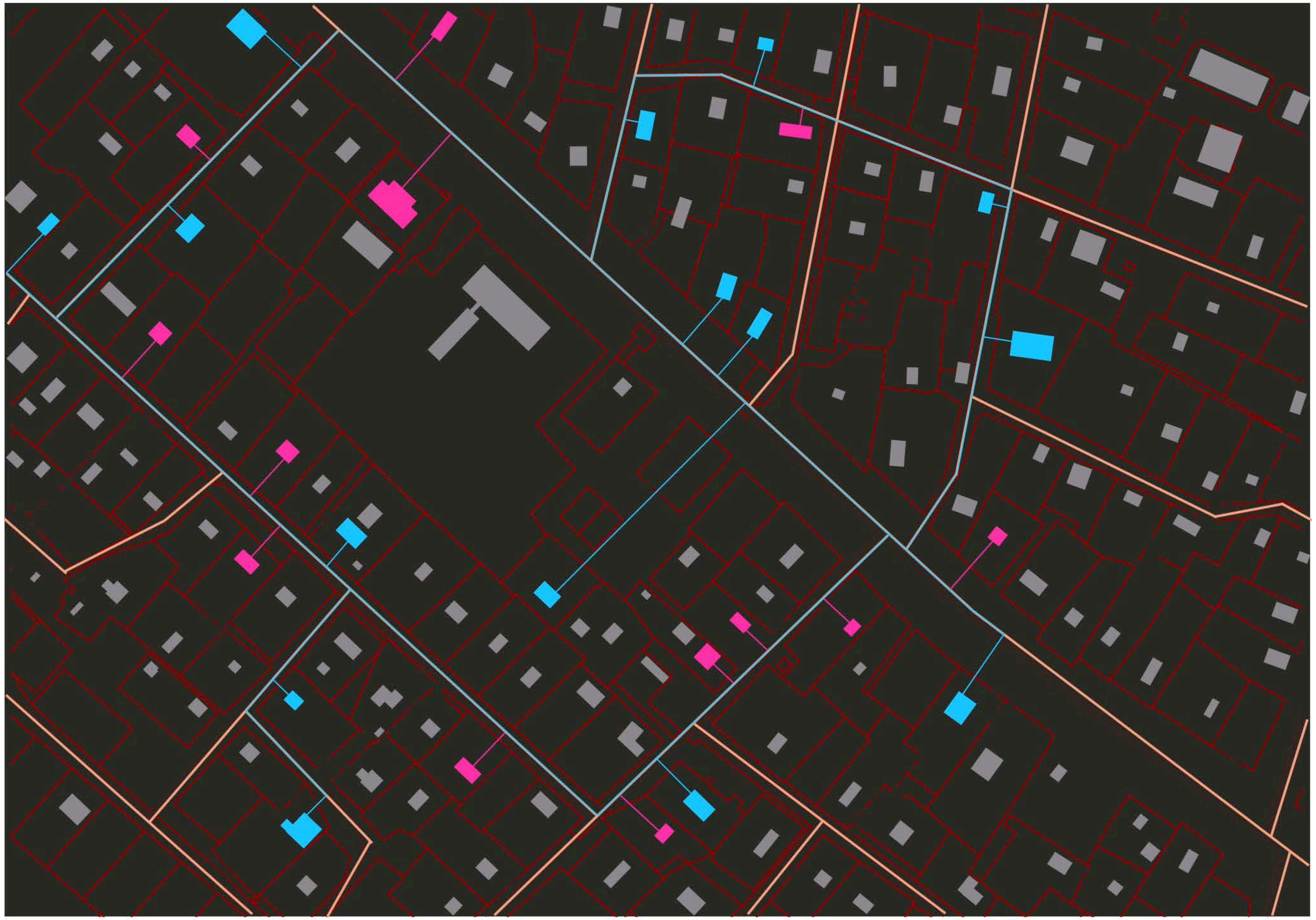
Local energy markets

… and consumers of renewable energy …



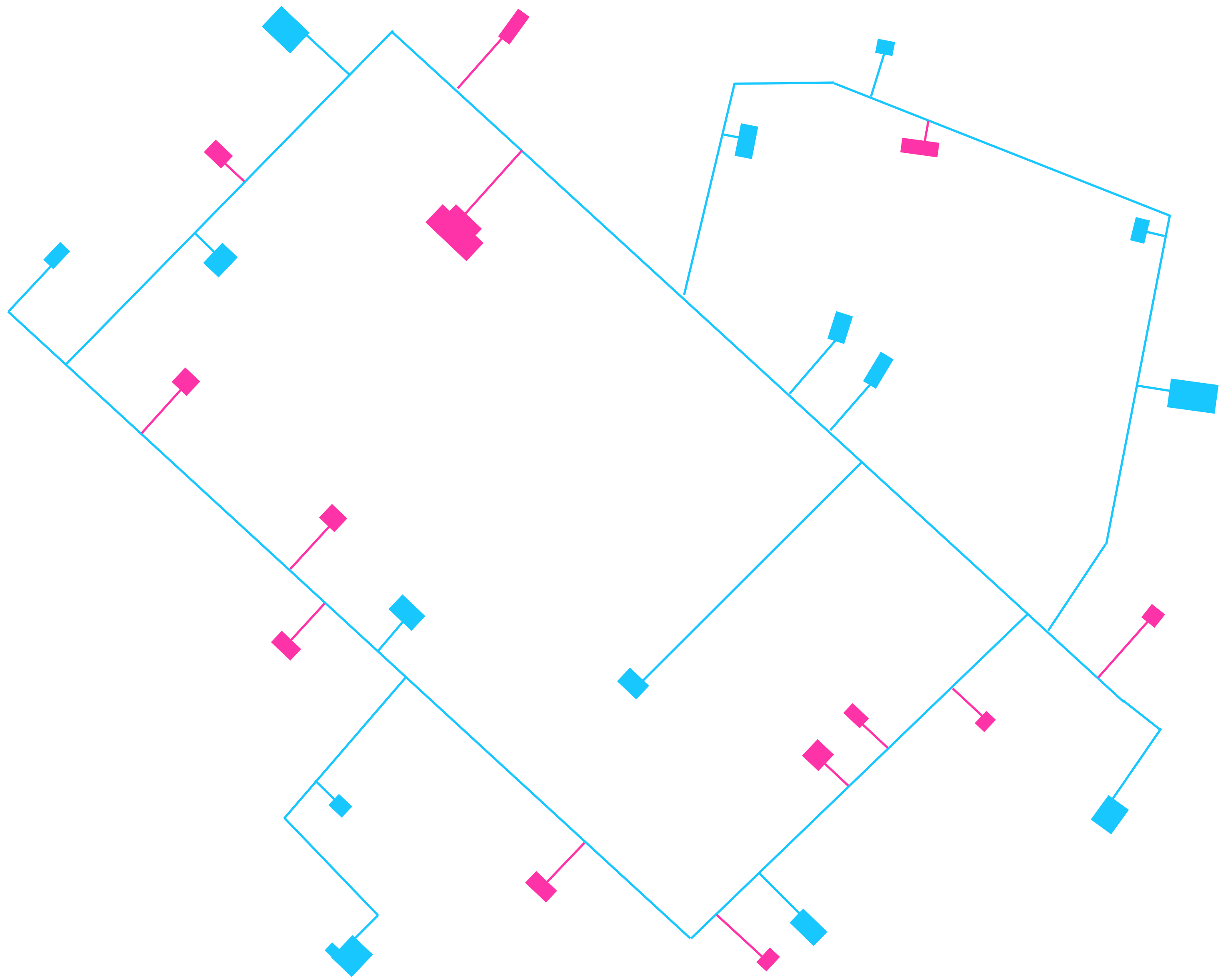
Local energy markets

… trade their energy on a local energy market.



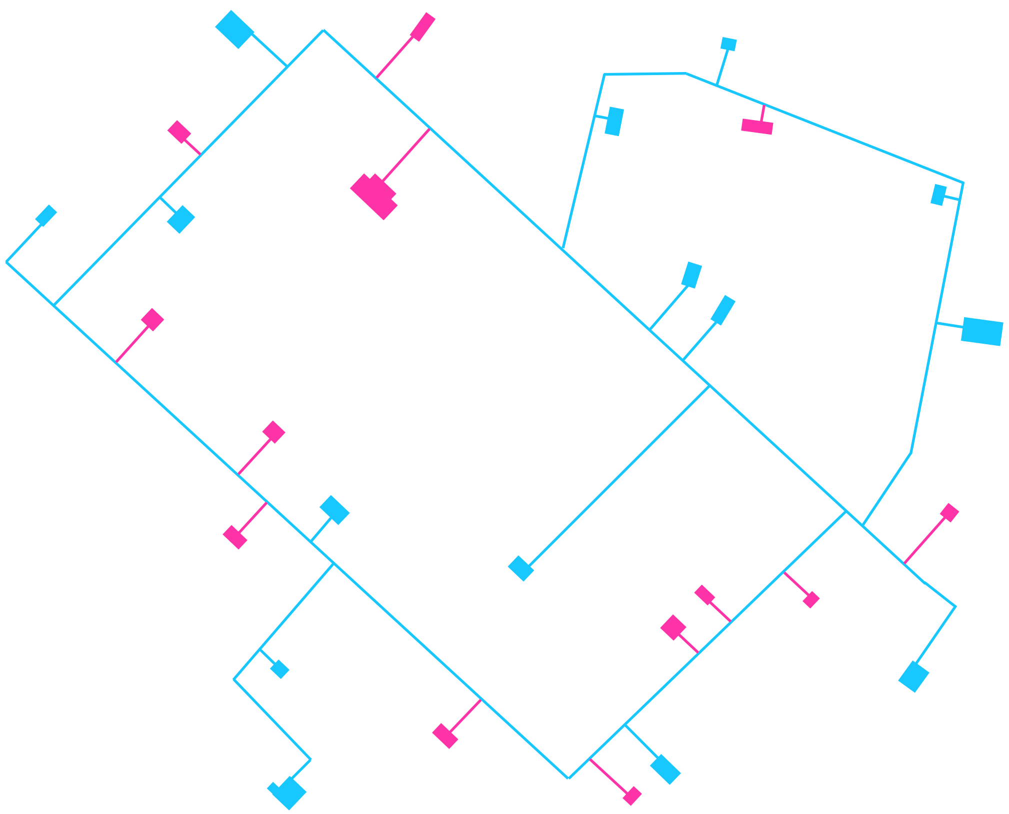
Local energy markets

Local energy market can be implemented on blockchain

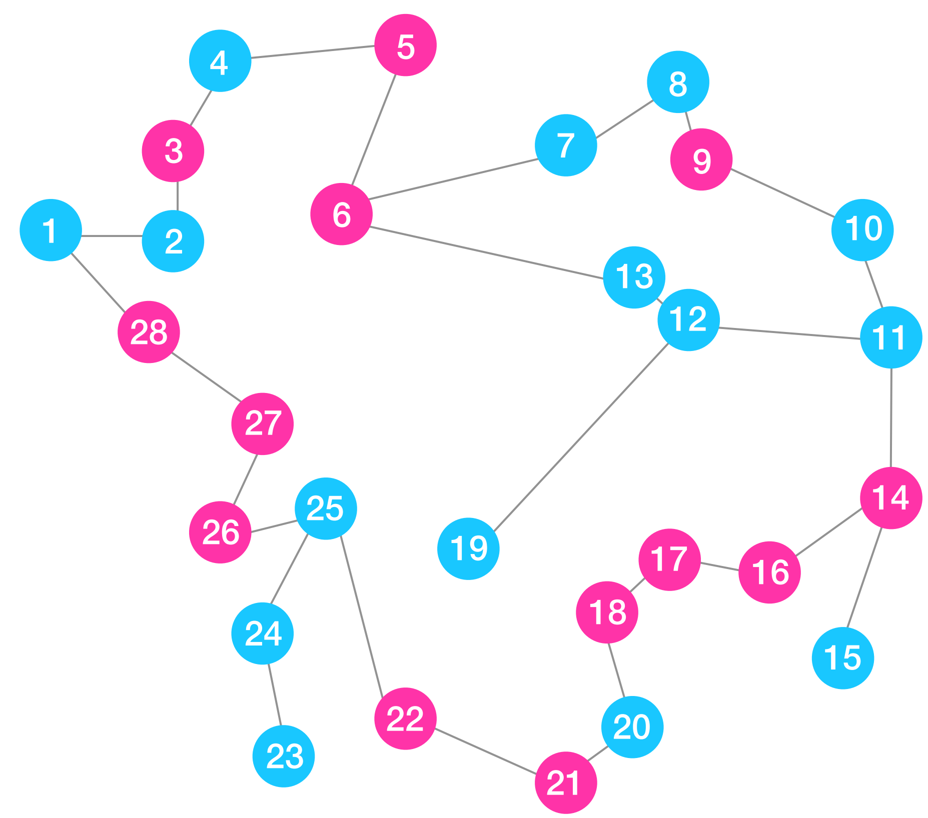


Local energy markets

Smart Grid configuration



Graph representation



Local energy markets

Adjacency matrix based on graph representation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0
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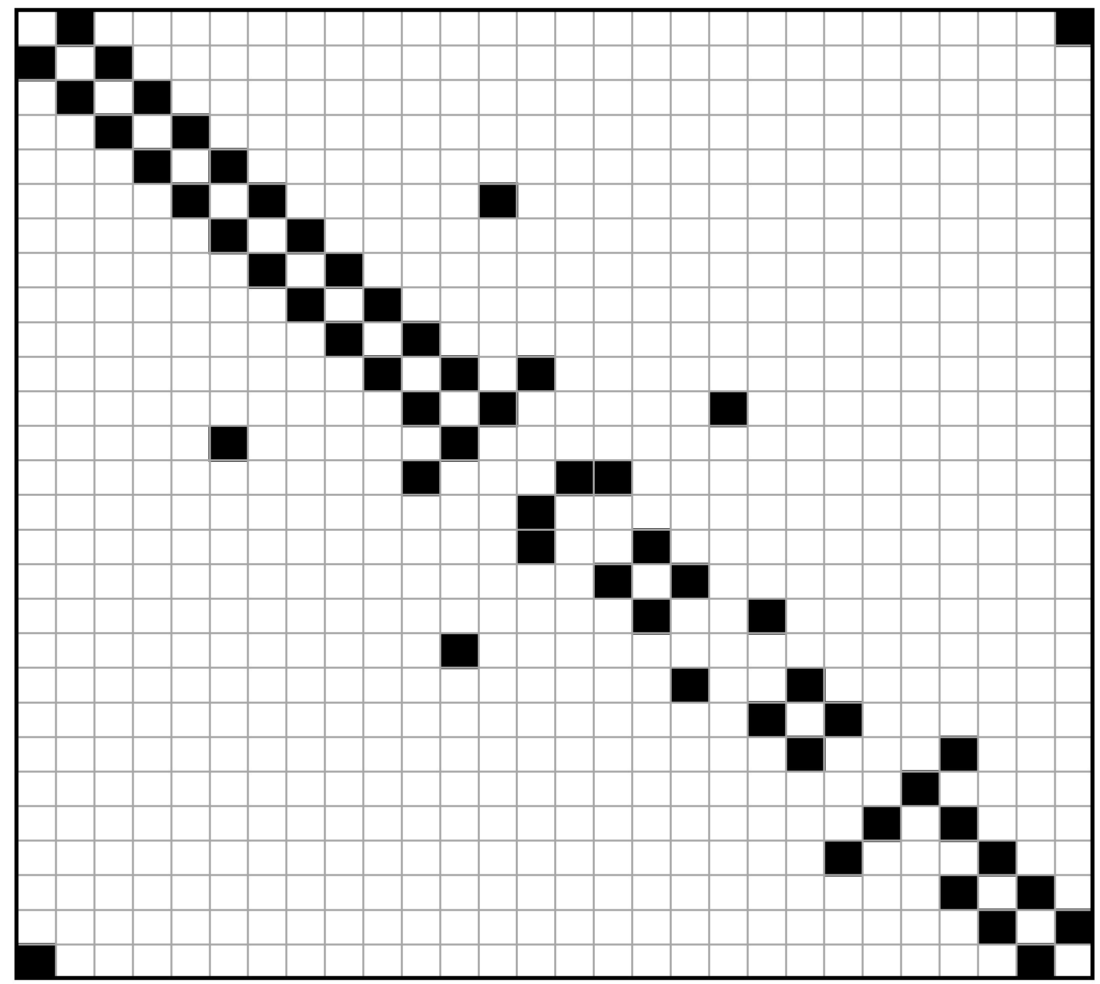
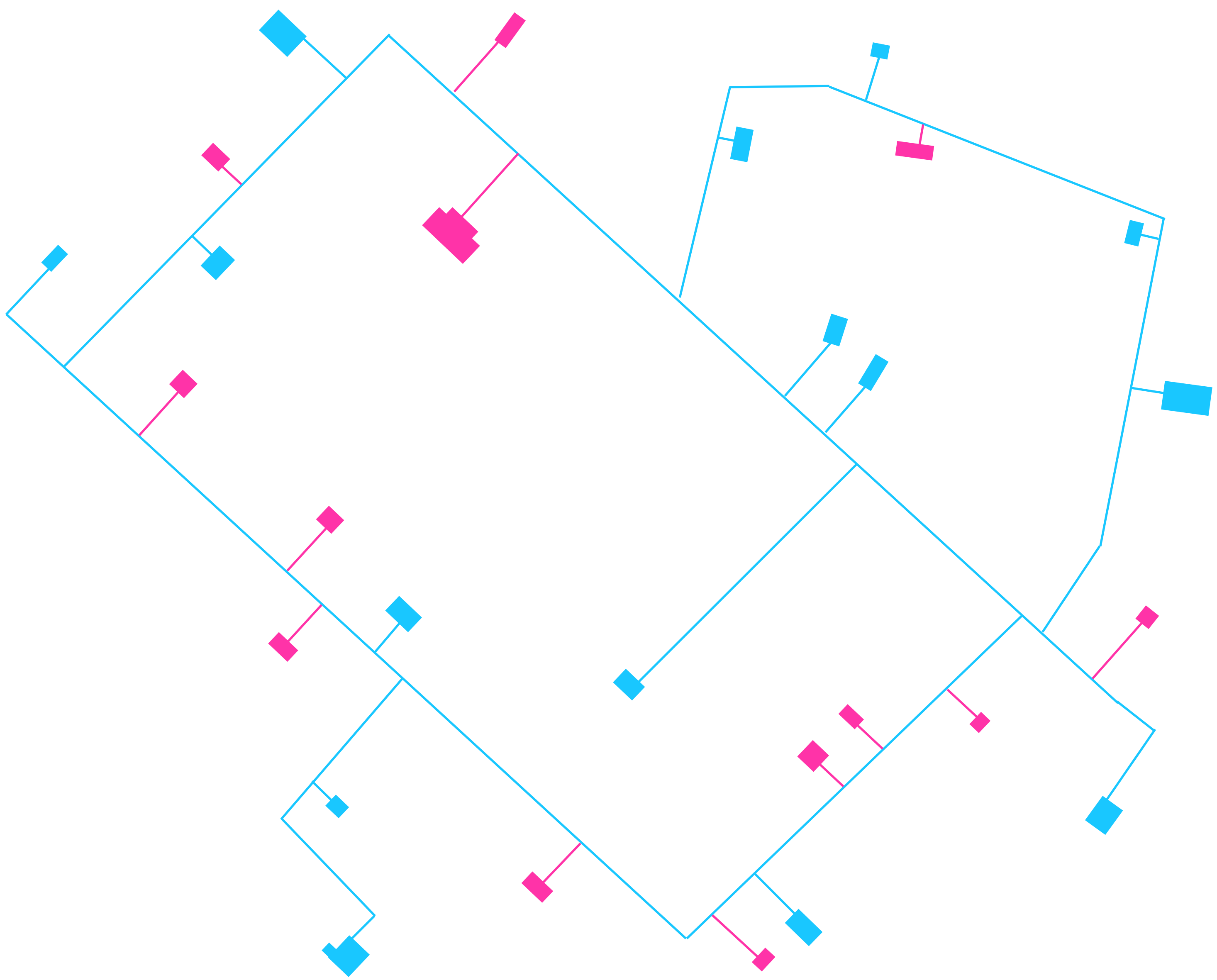
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
28	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0



Local energy markets

Industry projects for blockchain-based LEM exist



Grid Singularity

powerpeers
energie voor elkaar

Power Ledger

LO3 ENERGY

Market mechanism as smart contract

- Smart meters forecast energy production and consumption
- Trading agents broadcast offer to sell or buy
- Smart contract matches offers at discrete market closing times
- Transactions according to actual supply and demand
- Forecasting errors settled at higher cost

Accurate forecasts

- Market participants' bids based on forecasts
- Equilibrium price computed by smart contract based on bids
- Settlement according to actual demand and supply
- Prediction errors cleared through energy utility at higher costs

$\succ$ Participation in LEM unprofitable in case of high prediction errors

Proposition

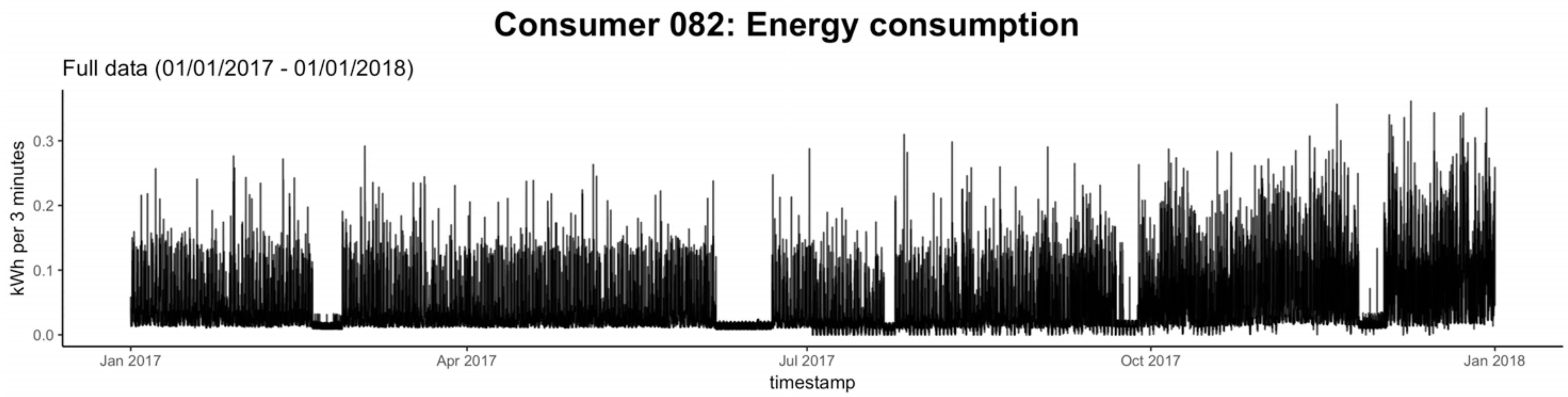
Blockchain-based local energy markets are one solution to the challenges of the energy transformation –

But without accurate energy forecasts for individual households, they may not be reasonable.

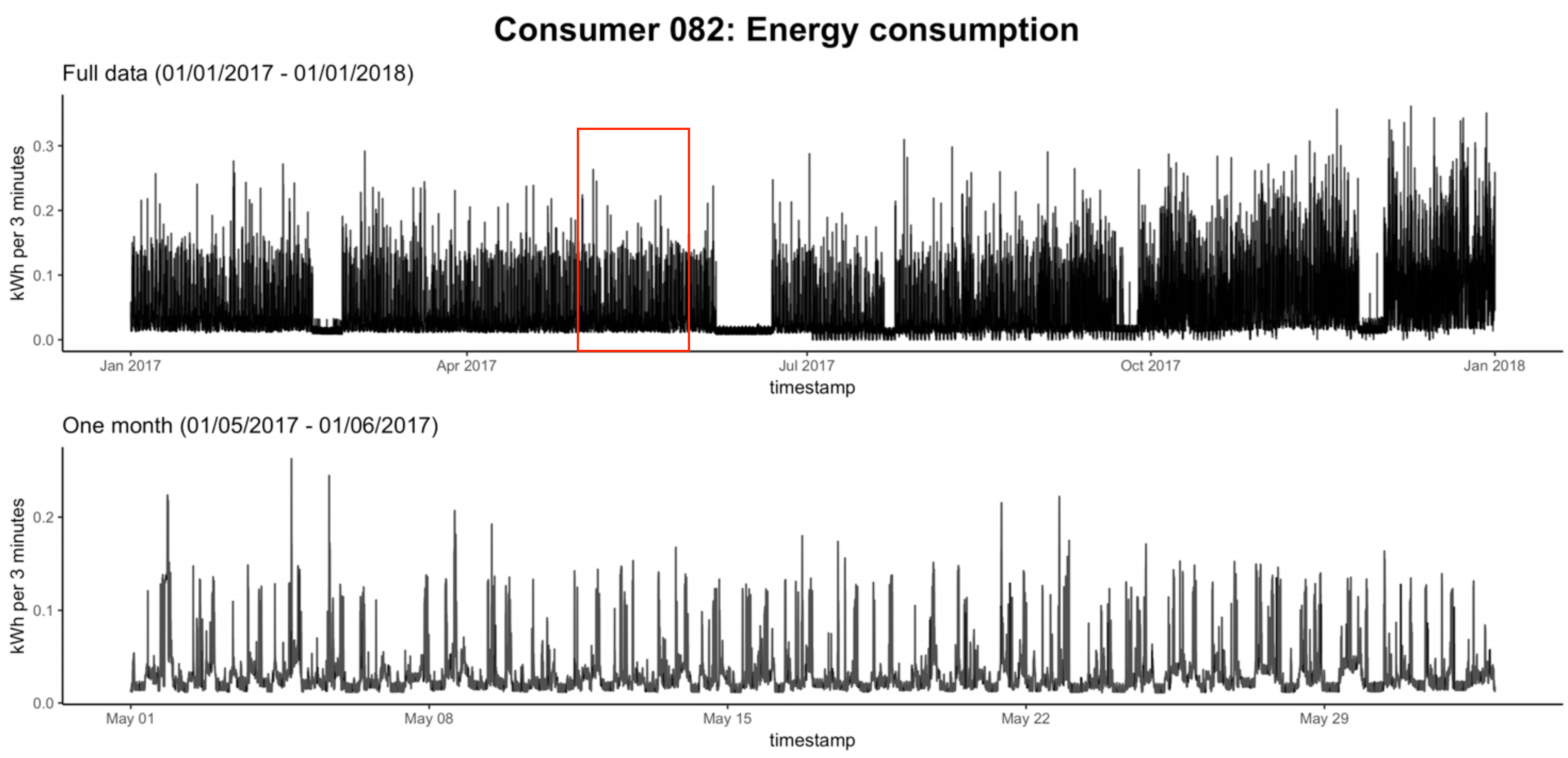
Forecast evaluation and market outcomes
- Data used

- Source: Discovergy GmbH
- Energy readings (in and out, i.e., consumption and production) recorded by smart meter in 2-seconds intervals; aggregated to 3-minutes intervals
- 100 consumer, 100 prosumer datasets
- 1 year (2017), i.e., 175.200 measurement points per smart meter
- Exclusion due to
  - High share of zero consumption values
  - Zero production values
  - Conspicuous consumption/production patterns
- Final sample: 88 consumers, 12 prosumers

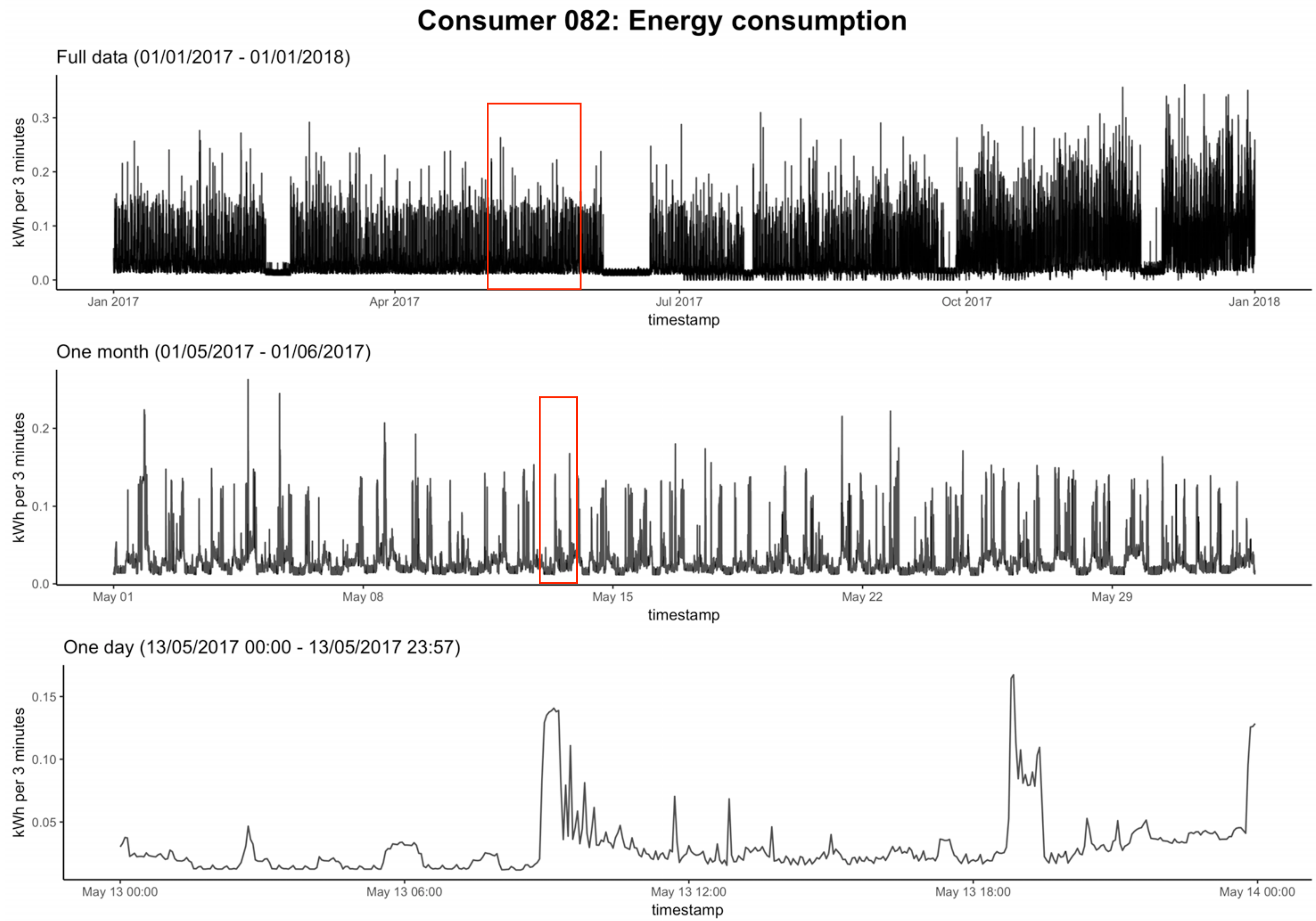
Forecast evaluation and market outcomes
- Data used



Forecast evaluation and market outcomes
- Data used



Forecast evaluation and market outcomes
- Data used



BLEMplotEnergyData

Forecast evaluation and market outcomes
- Forecasting methods

- Energy time series of households highly volatile with high degree of uncertainty
- Classical time series modelling techniques unsuccessful
- Successful approaches derived from literature
- Forecasting methods used:
  - Benchmark: Naïve persistence model $\hat{x}_{t+1} = x_t$
  - Long-short term memory recurrent neural network (based on Shi et al., 2017)
  - Autoregressive LASSO (based on Li et al., 2017)

Forecast evaluation and market outcomes
- Forecasting method: LSTM RNN

- Developed by Hochreiter & Schmidhuber, 1997
- Specification

$$\mathbf{i}_t = \sigma\left(\mathbf{W}^{(ix)}\mathbf{x}_t + \mathbf{W}^{(is)}\mathbf{s}_{t-1} + \mathbf{b}_i\right)$$
$$\mathbf{f}_t = \sigma\left(\mathbf{W}^{(fx)}\mathbf{x}_t + \mathbf{W}^{(fs)}\mathbf{s}_{t-1} + \mathbf{b}_\mathbf{f}\right)$$
$$\mathbf{o}_\mathbf{t} = \sigma\left(\mathbf{W}^{(\mathbf{ox})}\mathbf{x}_\mathbf{t} + \mathbf{W}^{(\mathbf{os})}\mathbf{s}_{\mathbf{t}-1} + \mathbf{b}_\mathbf{o}\right)$$
$$\mathbf{g}_t = \sigma\left(\mathbf{W}^{(gx)}\mathbf{x}_t + \mathbf{W}^{(gh)}\mathbf{h}_{t-1} + \mathbf{b}_g\right)$$
$$\mathbf{s}_t = \mathbf{g}_t \odot \mathbf{i}_t + \mathbf{s}_{t-1} \odot \mathbf{f}_t$$
$$\mathbf{h}_t = \phi\left(\mathbf{s}_t\right) \odot \mathbf{o}_t$$

- Implementation
  - Input data: Energy consumption/production in log-kWh per 3 minutes scaled between 0 and 1
    Dummy vectors with one-hot encoding of weekends and holidays
  - Lookback: 3,360 data points (1 week)
  - Batch size: 32
  - Target: 1 value (energy consumption/production in kWh per 15 minutes)
  - Hidden units: 32
  - Training samples: 700 (à 32 x 3,360 data points)

Forecast evaluation and market outcomes
- Forecasting method: LASSO

- Developed by Tibshirani, 1996
- Objective function

$$\min_{(\beta_0,\beta)} \frac{1}{2N} \sum_{i=1}^{N} (y_i - \beta_0 - x_i^T \beta)^2 + \lambda \parallel \beta \parallel_1$$

- Implementation
  - Predictors: 3,360 lags (energy consumption/production in kWh per 3 minutes)
  - Target: 1 value (energy consumption/production in kWh per 15 minutes)
  - Training samples: 22,400 (sliding windows with 5-observations skip)
  - 10-fold cross-validation

Forecast evaluation and market outcomes

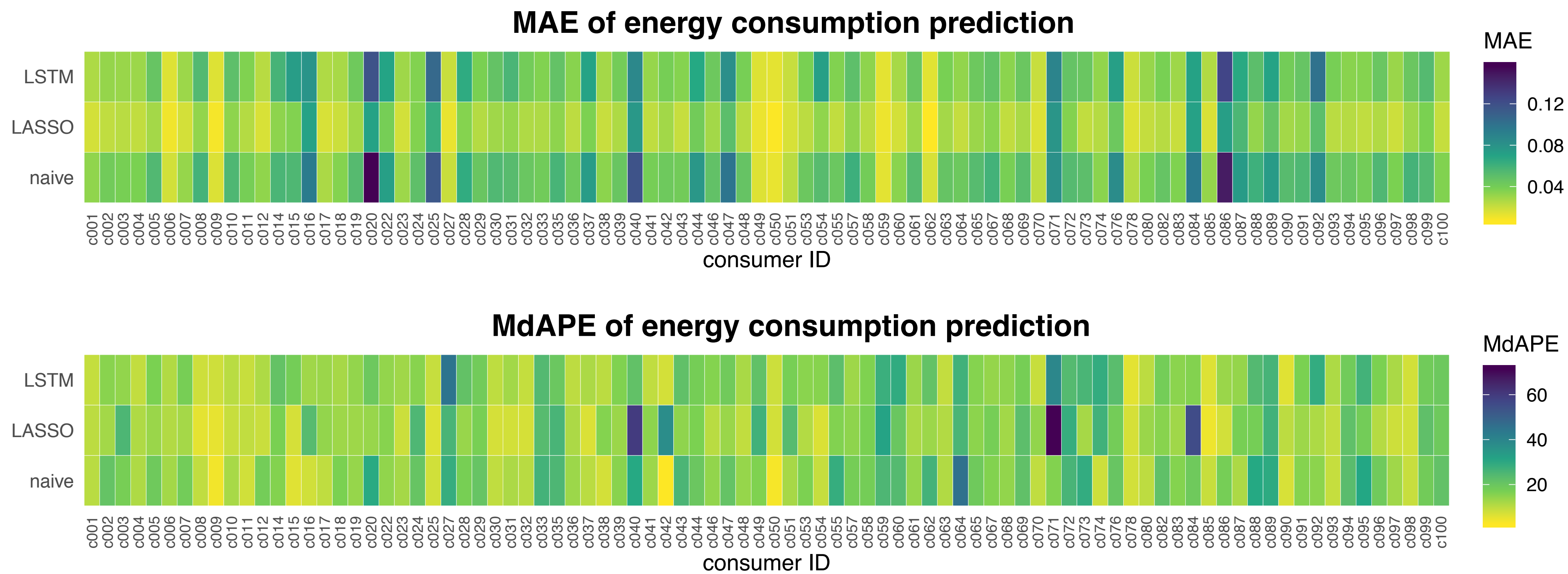
- Forecasting results

Model	MAE	RMSE	MAPE	NRMSE	MASE
LSTM	0.04	0.09	22.22	3.30	0.85
LASSO	0.03	0.05	17.38	2.31	0.57
Benchmark	0.05	0.10	27.98	5.08	1.00
Improvement LSTM (in %)	16.21	12.61	20.57	34.98	14.78
Improvement LASSO (in %)	44.02	48.73	37.88	54.61	43.02

Median of error measures for the prediction of energy consumption across all 88 consumer data sets.

BLEMevaluateEnergyPreds

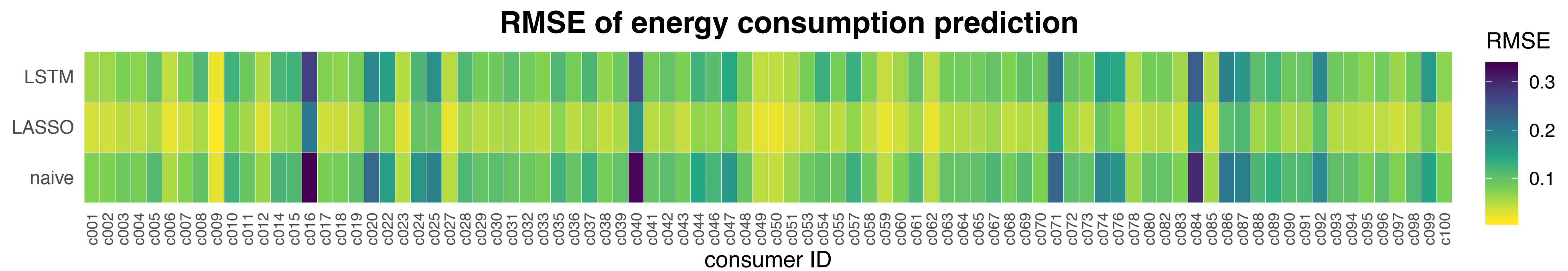
Forecast evaluation and market outcomes
- Forecasting results

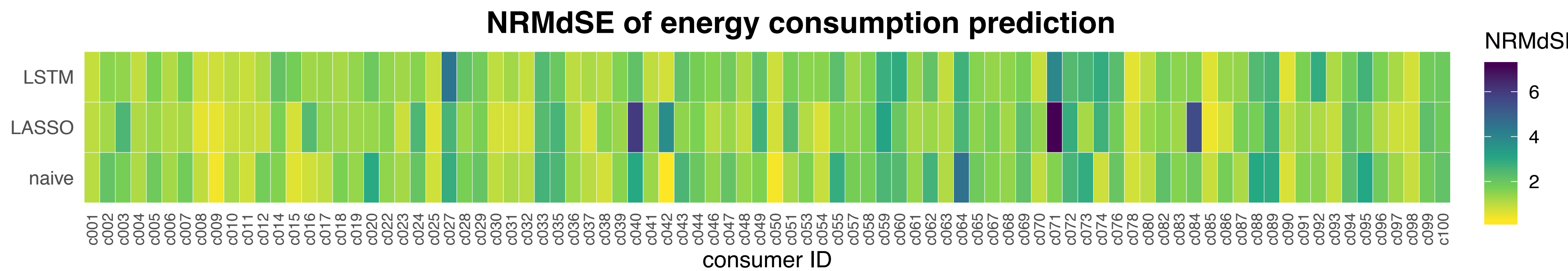


Mean absolute error and median absolute percentage error for each prediction method on each consu-mer dataset.

QBLEMevaluateEnergyPreds

Forecast evaluation and market outcomes
- Forecasting results





Root mean squared error and normalised root median squared error for each prediction method on each consumer data set.

BLEMet.evaluateEnergyPreds

Interim conclusion:

LASSO regression can make reasonably accurate energy forecasts for individual households –

But are they accurate enough for blockchain-based local energy markets?

Forecast evaluation and market outcomes
- Market outcomes

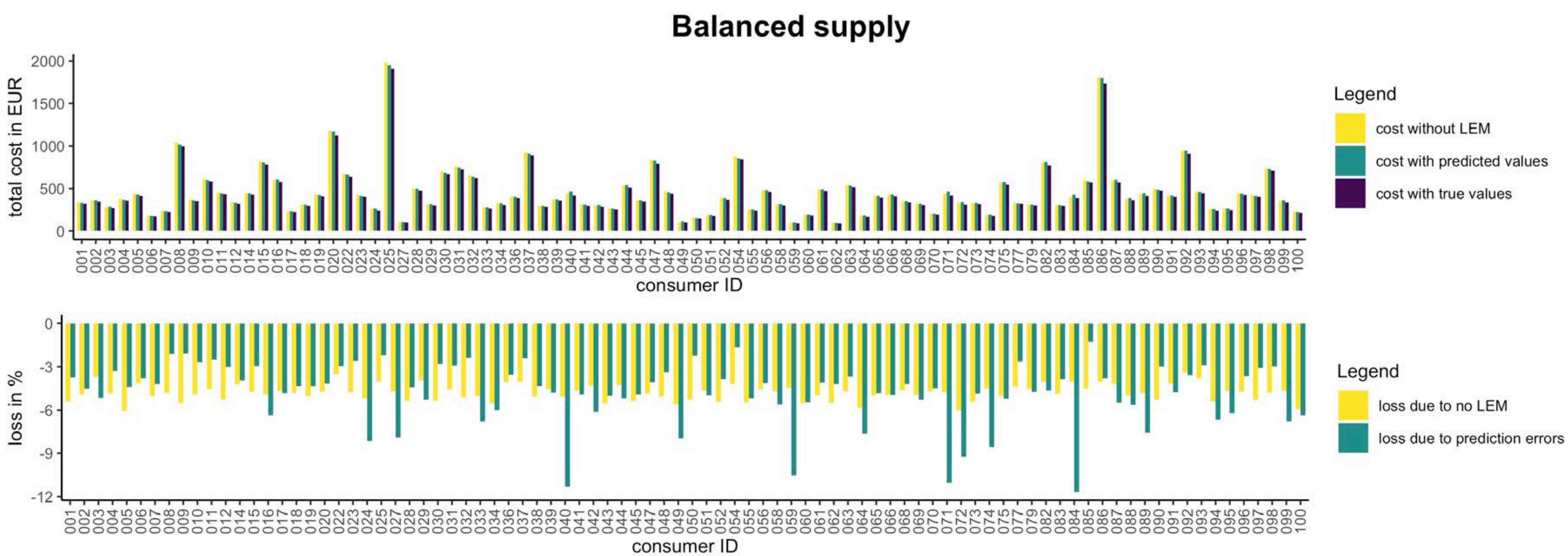
- Market mechanism replicates smart contract by Mengelkamp et al. (2018)
- Comparing market outcomes using true and predicted consumption values
- Testing period: 01.10.2017 – 31.12.2017 (8,836 15-minutes trading slots)
- Market mechanism: Blind double auction with discrete market closing times
- 3 supply scenarios
  - Balanced supply: 7 producers
  - Oversupply: 9 producers
  - Undersupply: 6 producers

Forecast evaluation and market outcomes
- Market outcomes

Mean	Balanced supply	Oversupply	Undersupply
Cost without LEM (in EUR)	459.83	459.83	459.83
Cost predicted values (in EUR)	457.94	226.61	470.69
Cost true values (in EUR)	439.26	200.75	451.60
Savings due to LEM (in %)	4.82	129.08	1.90
Loss due to pred. errors (in %)	−4.80	−13.75	−4.76

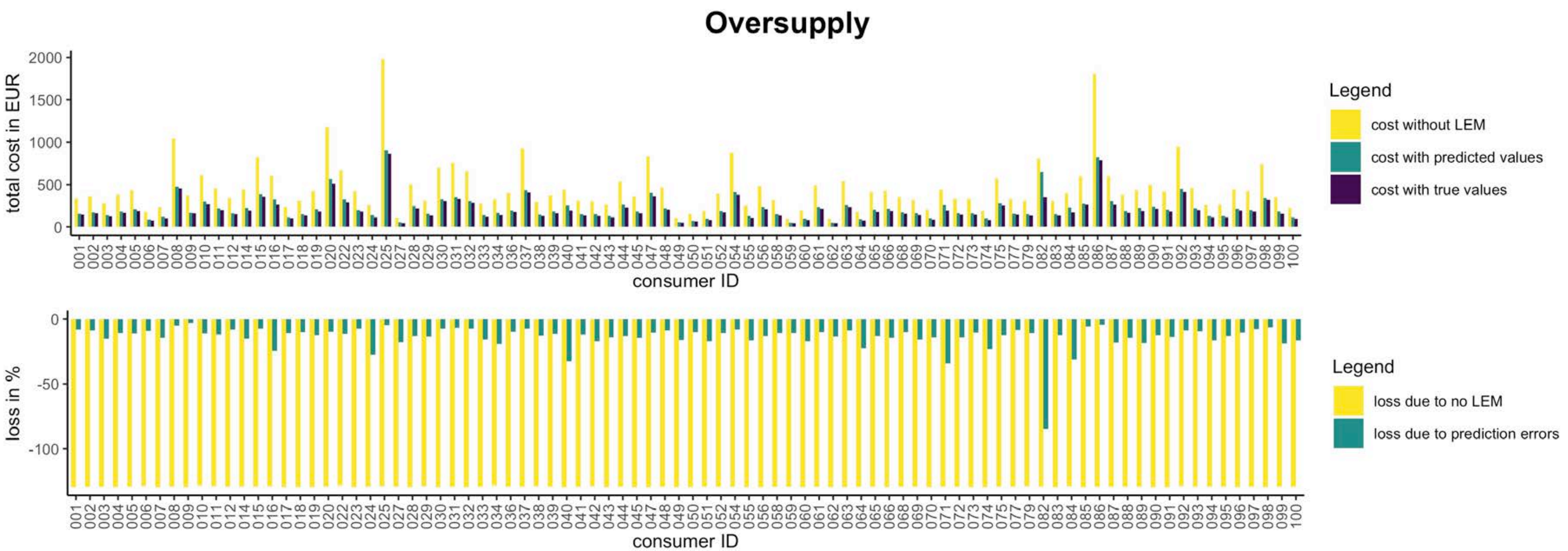
Average savings for consumers due to LEM and average loss for consumers due to prediction errors for consumption foreca in LEM. BLEMEvaluateMarketSim

Forecast evaluation and market outcomes
- Market outcomes



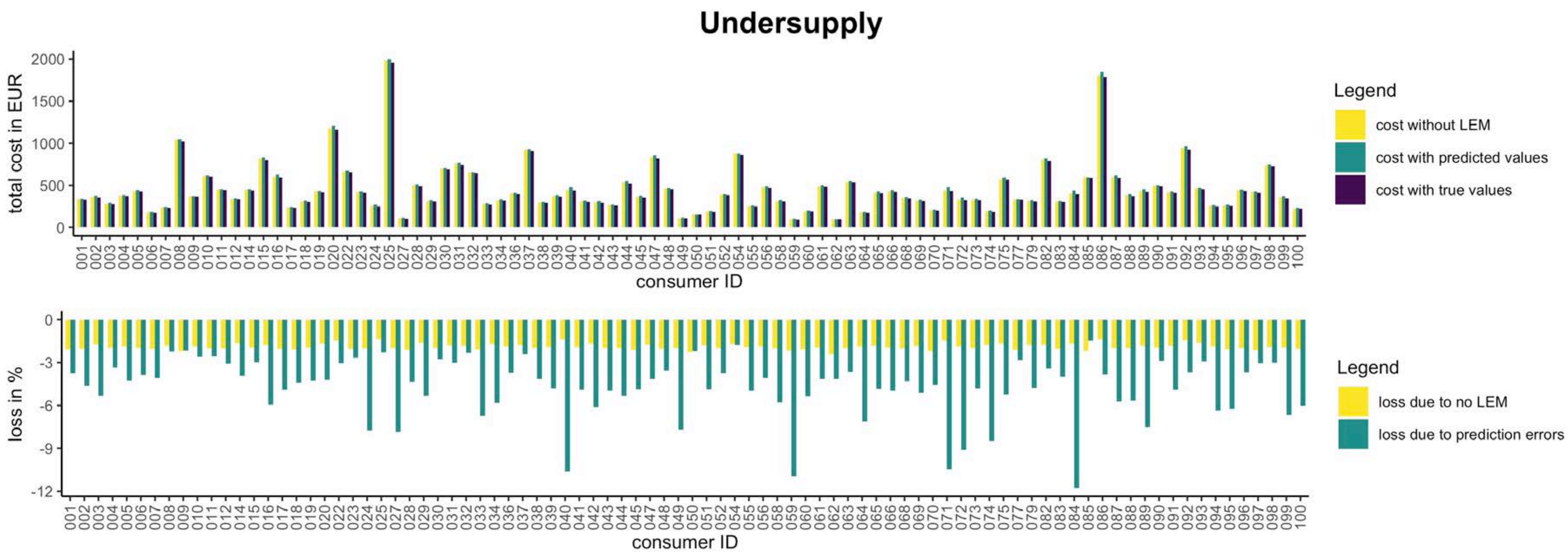
Total energy cost to consumers from 01.10.2018 to 31.12.2017 in case of no LEM, LEM with true values, and LEM with predicted values in balanced supply scenario. LEM.evaluateMarketSim

Forecast evaluation and market outcomes
- Market outcomes



Total energy cost to consumers from 01.10.2018 to 31.12.2017 in case of no LEM, LEM with true values, and LEM with predicted values in oversupply scenario. BLEMevaluateMarketSim

Forecast evaluation and market outcomes
- Market outcomes



Total energy cost to consumers from 01.10.2018 to 31.12.2017 in case of no LEM, LEM with true values, and LEM with predicted values in undersupply scenario. BLEM.evaluateMarketSim

Better forecasts or different market mechanism

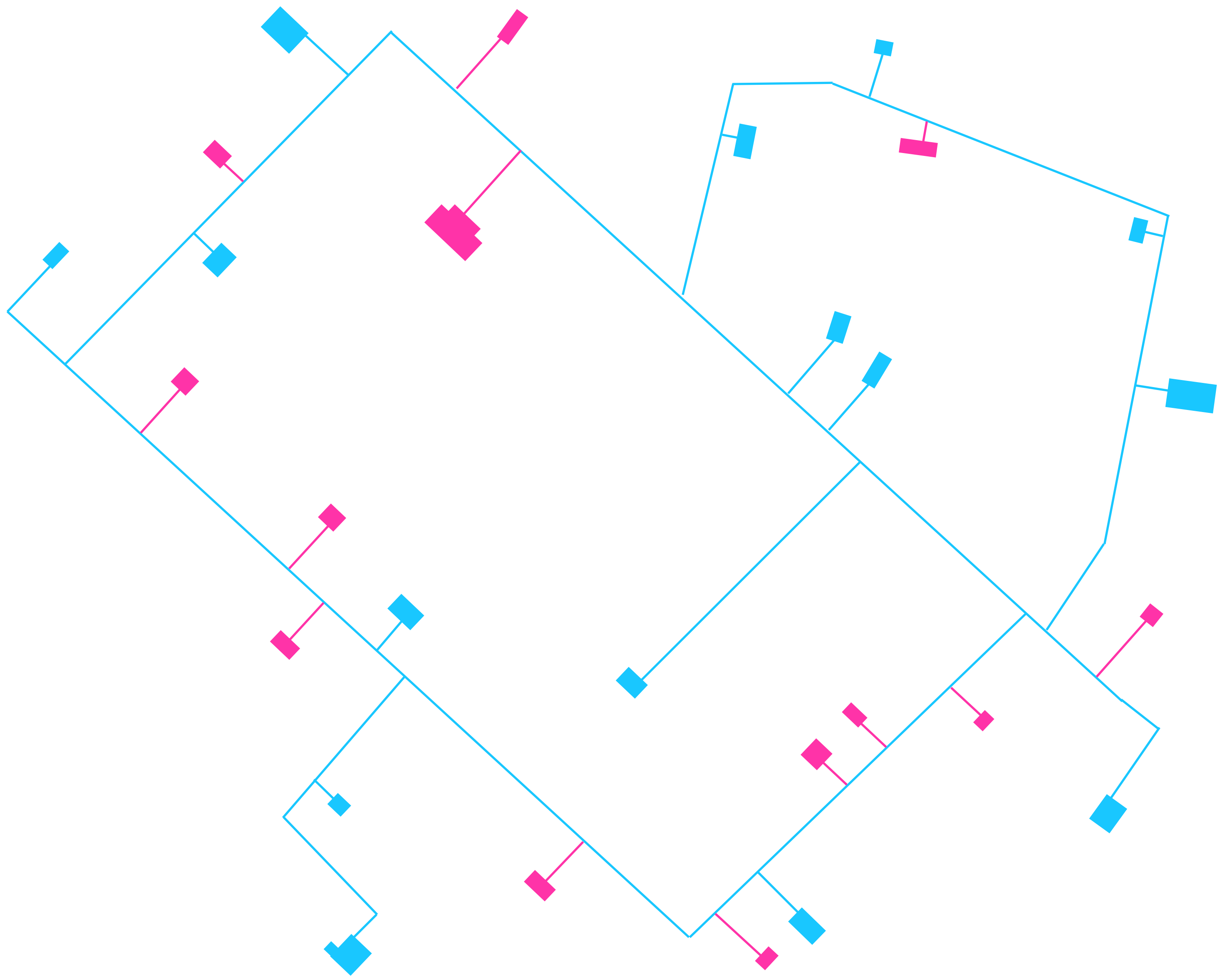
- Local energy markets bring savings to consumers with accurate energy consumption forecasts
- Substantial prediction errors in individual household energy consumption forecasts
- LEM uneconomical for consumers without oversupply given prediction errors
- Options to mitigate problem:
  1. More accurate forecasts ≻ More data needed
     - Problem: Increases privacy concerns
  2. Different market mechanism ≻ Shorter time intervals or exposed market
     - Problem 1: Increases computational costs for smart contract execution
     - Problem 2: Susceptible for fraud and “gaming” the mechanism

Final conclusion:

Prediction errors can make blockchain-based local energy markets unsuitable to solve our energy landscape transformation challenges –

But current research does not take this into account.

Future research should.



Appendix

General advantages of LEM

- Local netting of energy demand and supply reduces uncertainty of local production and consumption (Block et al., 2007)
- National-level market prices due not reflect local production scarcity or oversupply (Nieß et al., 2012)
- Local trading enables near real-time pricing of local production (Mengelkamp et al., 2017a)
- Possible energy cost reduction (Brooklyn Microgrid, 2016)
- Retainment of profits within community encourages further investment in renewable energy sources (Mengelkamp et al., 2017b)
- LEM empower communities of energy producers and consumers and offer more choice regarding energy suppliers (Mengelkamp et al., 2017a)

Additional advantages of LEM on Blockchain

- User-friendliness through automation and transparency (Mengelkamp et al., 2017a)
- No central intermediary/authority needed (Mengelkamp et al., 2017a)
- Near real-time settlement of financial transactions (Mihaylov et al., 2014)
- Smart contracts can be transparently audited and are guaranteed to be correctly executed by network (Munsing et al., 2017)

Research questions

a) Which prediction technique yields the best 15-minute ahead forecast for smart meter time series measured in 3-minute intervals using only input features generated from the historical values of the time series and calendar-based features?

b) Assuming a forecasting error settlement structure as described in Mengelkamp et al. (2018), what is the quantified loss of households participating in the local energy market due to forecasting errors by the prediction technique identified in a)?

c) Depending on the results from b), what implications and potential adjustments for the market mechanism described in Mengelkamp et al. (2018) can be identified?

Data I - Sample extracts

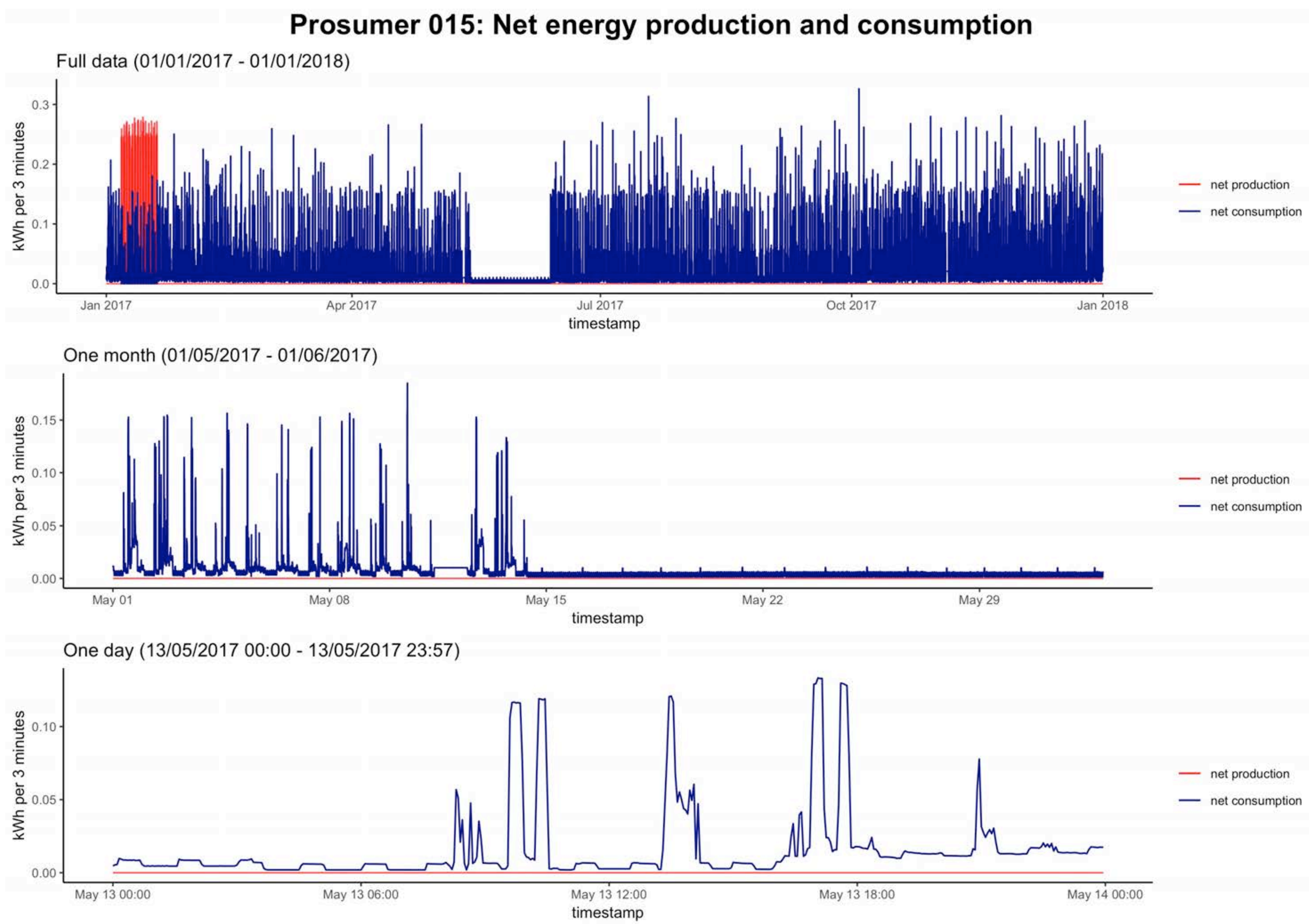
time	c056_energy	c056_power	c056_energyOut
20/09/2017 12:18	394685904516710	482151	0
20/09/2017 12:21	394686140477774	471922	0
20/09/2017 12:24	394686383717742	486480	0
20/09/2017 12:27	394686663010827	558586	0
20/09/2017 12:30	394686968990416	611959	0
20/09/2017 12:33	394687278165895	618351	0

Table 1: Sample extract of smart meter readings of consumer 056 (unit of energy is 1×10^{-10} kWh, unit of power is 1×10^{-3} W). BLEMdataGlimpse

time	p089_energy	p089_power	p089_energyOut
20/09/2017 12:18	528535857000	-5393732	353742266213493
20/09/2017 12:21	528535857000	-5392731	353744962578988
20/09/2017 12:24	528535857000	-5392900	353747659028946
20/09/2017 12:27	528535857000	-5394946	353750356501928
20/09/2017 12:30	528535857000	-5396914	353753054959007
20/09/2017 12:33	528535857000	-5394893	353755752405269

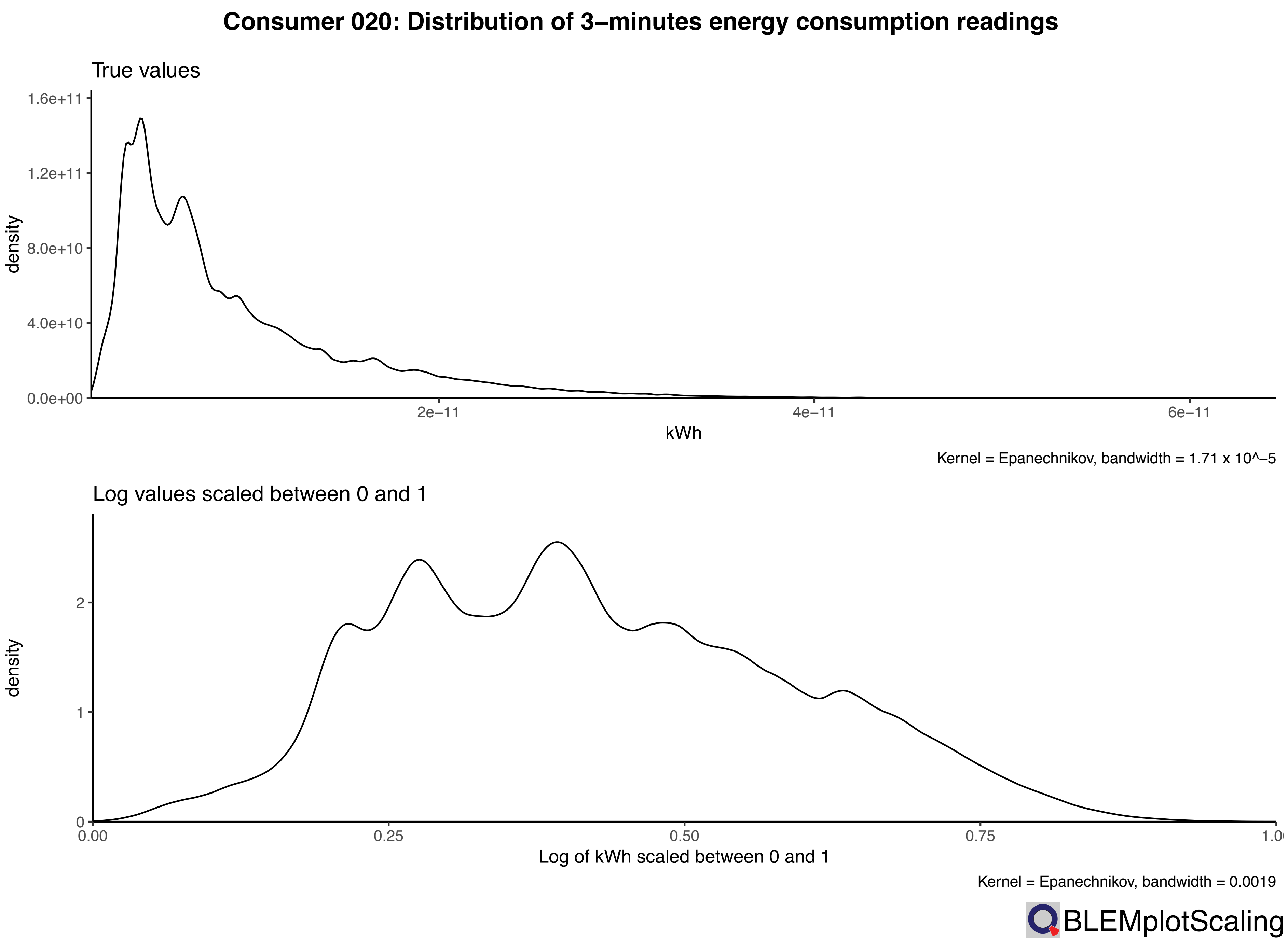
Table 2: Sample extract of smart meter readings of prosumer 089 (unit of energy is 1×10^{-10} kWh, unit of power is 1×10^{-3} W). BLEMdataGlimpse

Data II - Exemplary prosumer

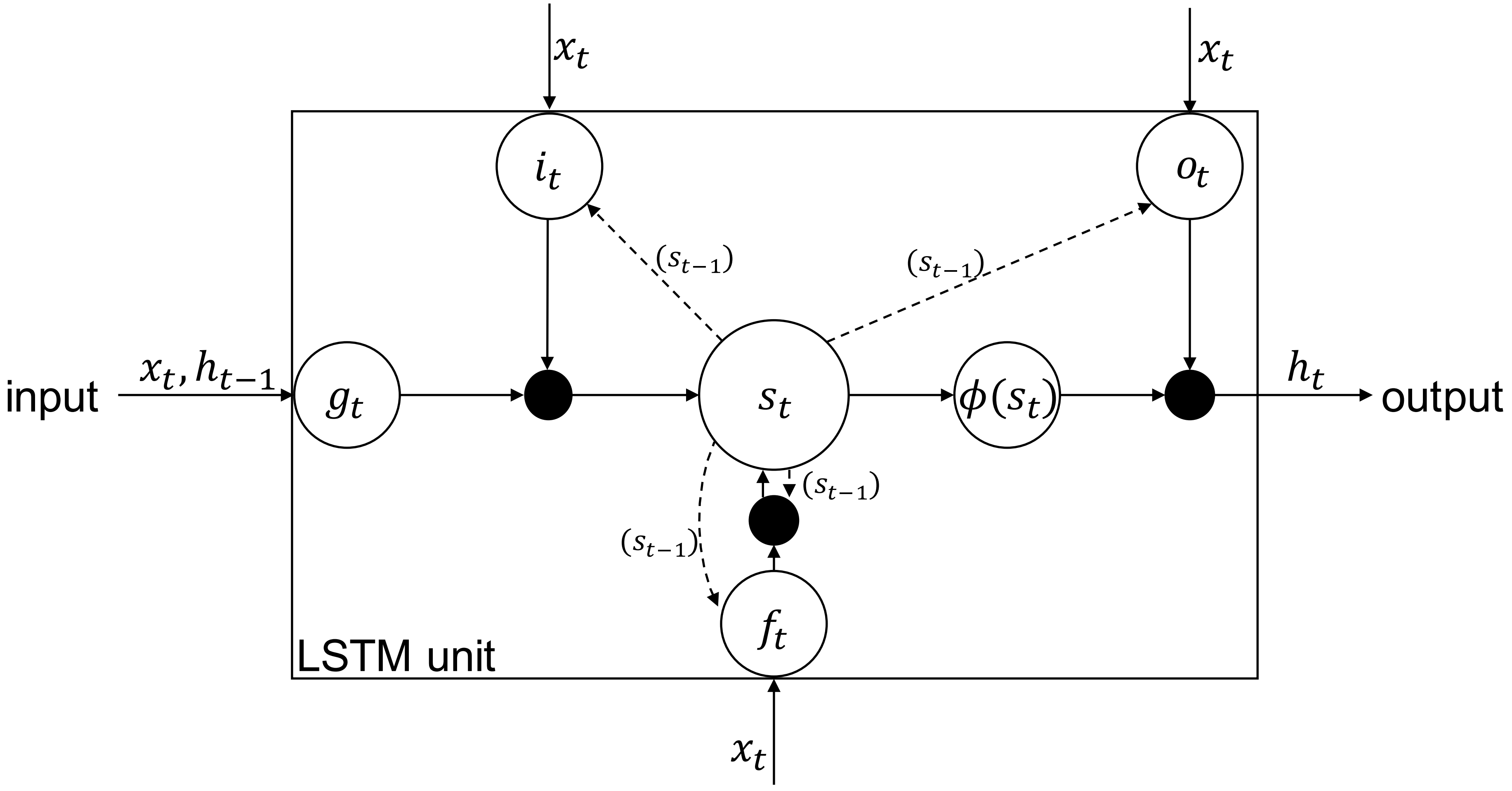


BLEMplotEnergyData

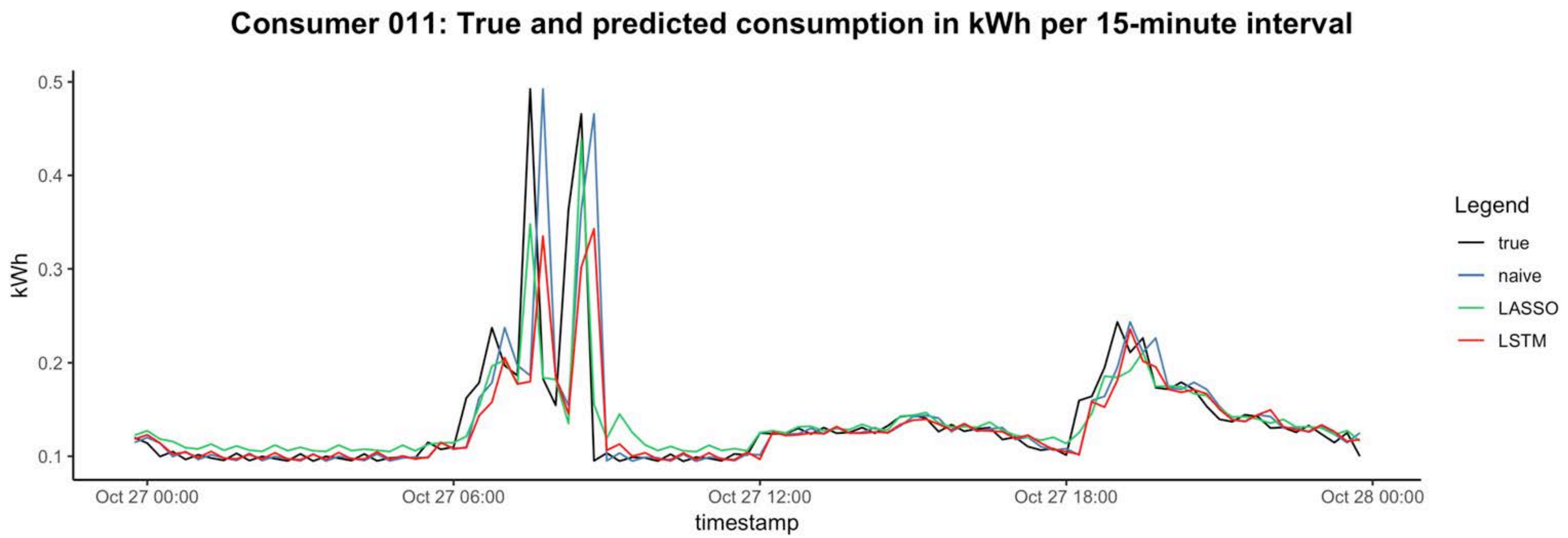
Data III – Example distribution and scaling for LSTM



LSTM unit with peephole connections (Gers et al., 2003)

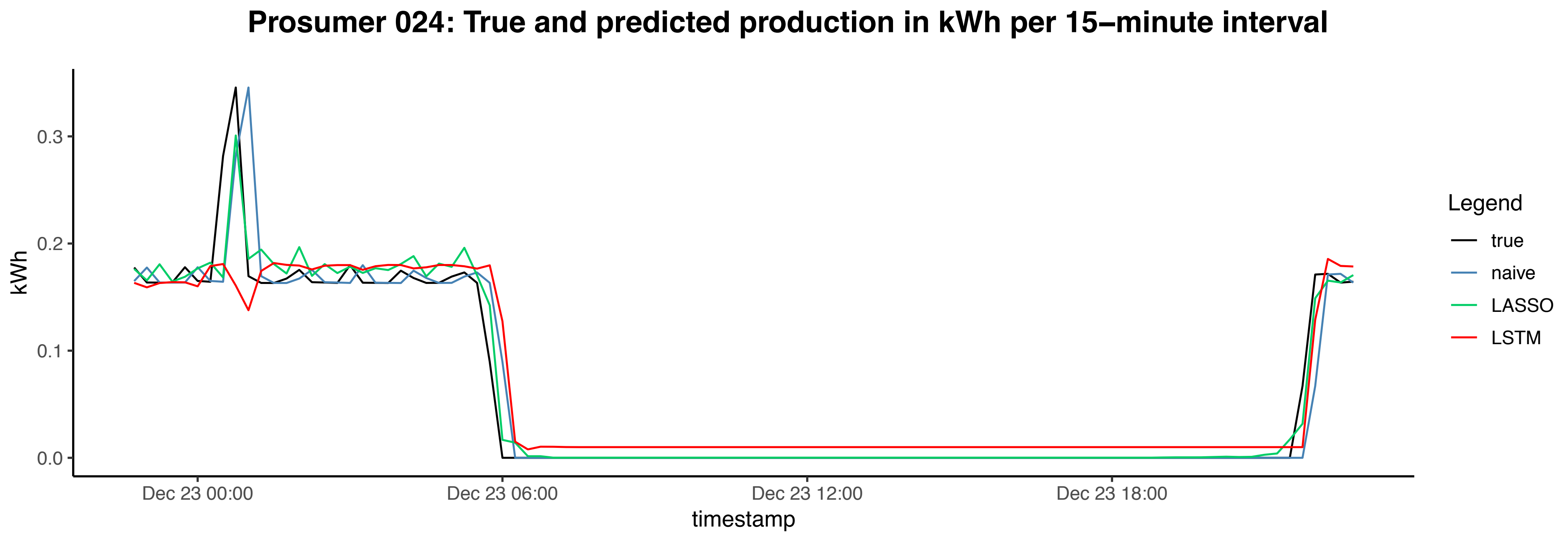


Sample forecast of consumption data



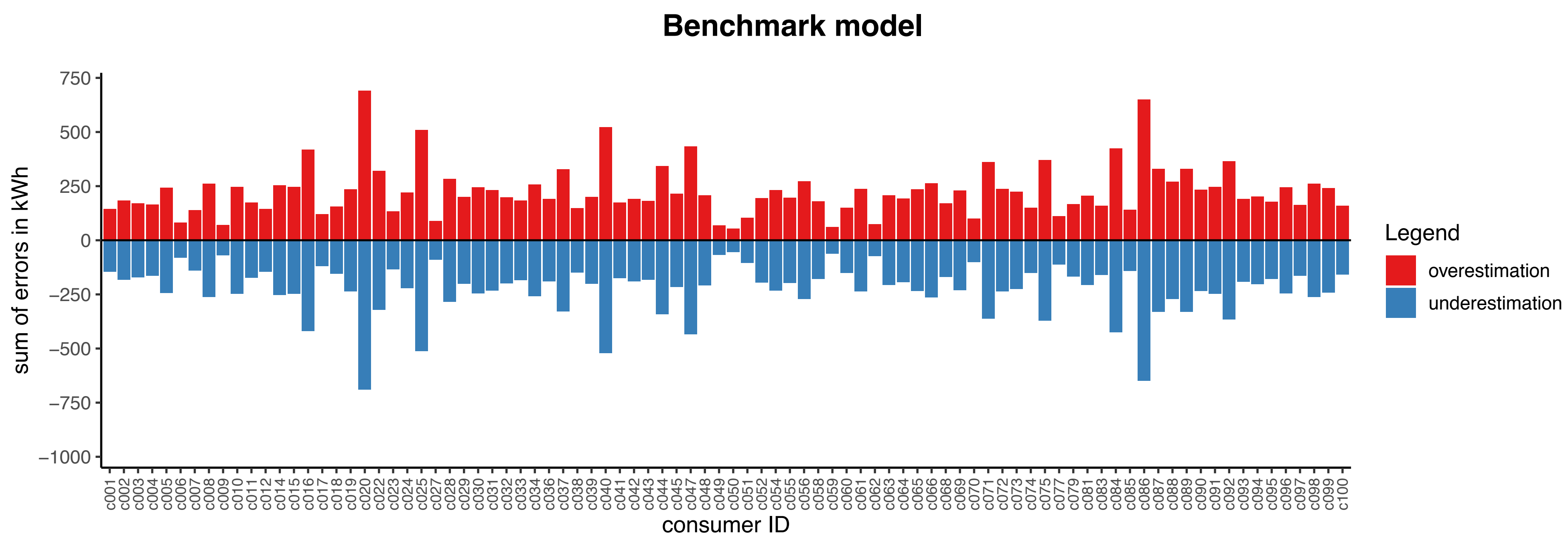
BLEMplotEnergyPreds

Sample forecast of production data



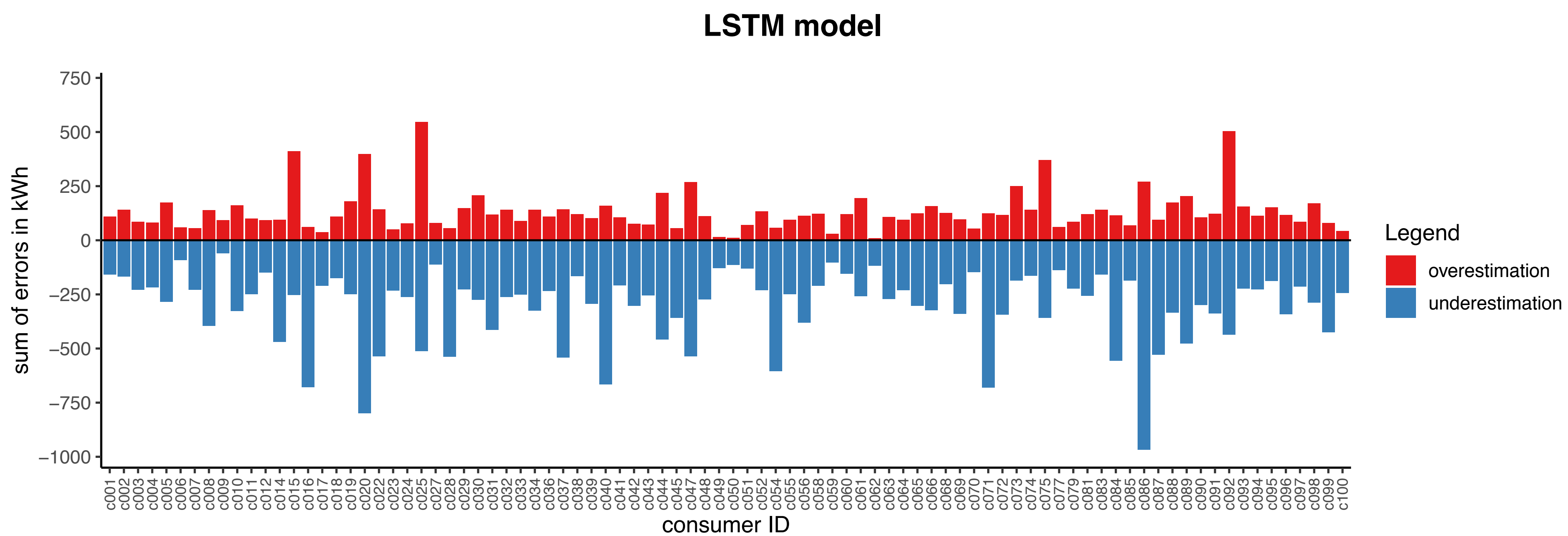
BLEMplotEnergyPreds

Over-/Underestimation errors of benchmark model on consumption data



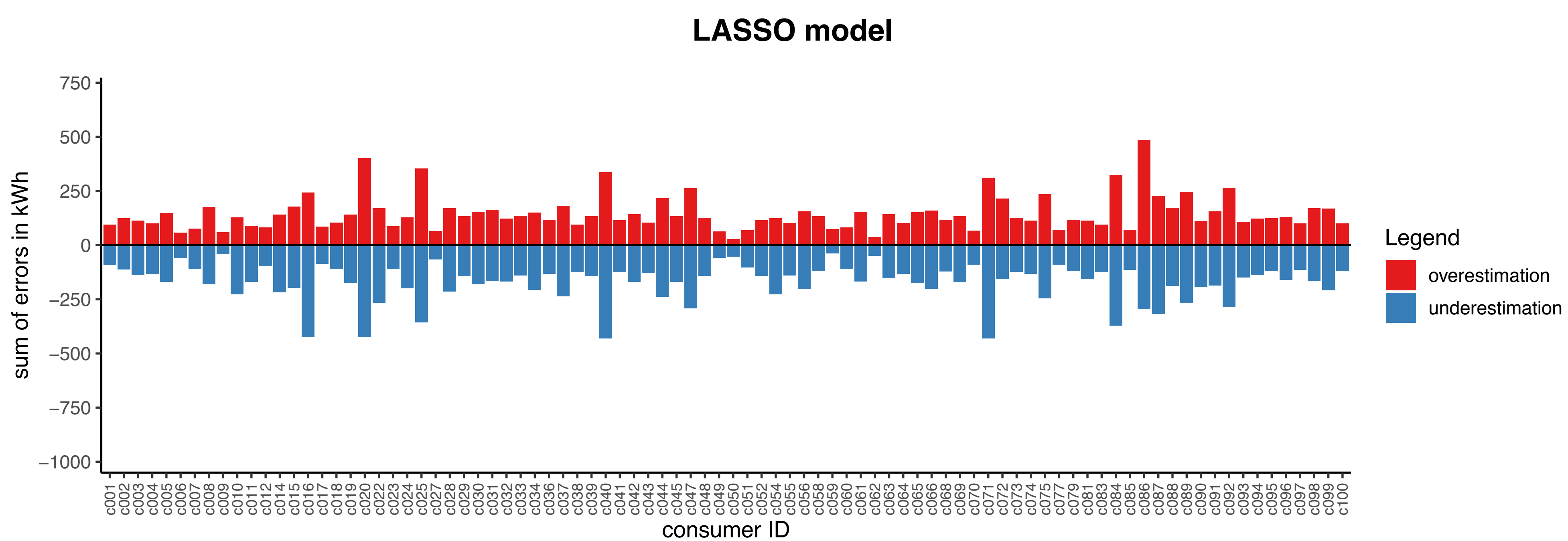
Sum of total over- and underestimation errors by benchmark model predicting energy consumption per consumer data set.

Over-/Underestimation errors of LSTM model on consumption data



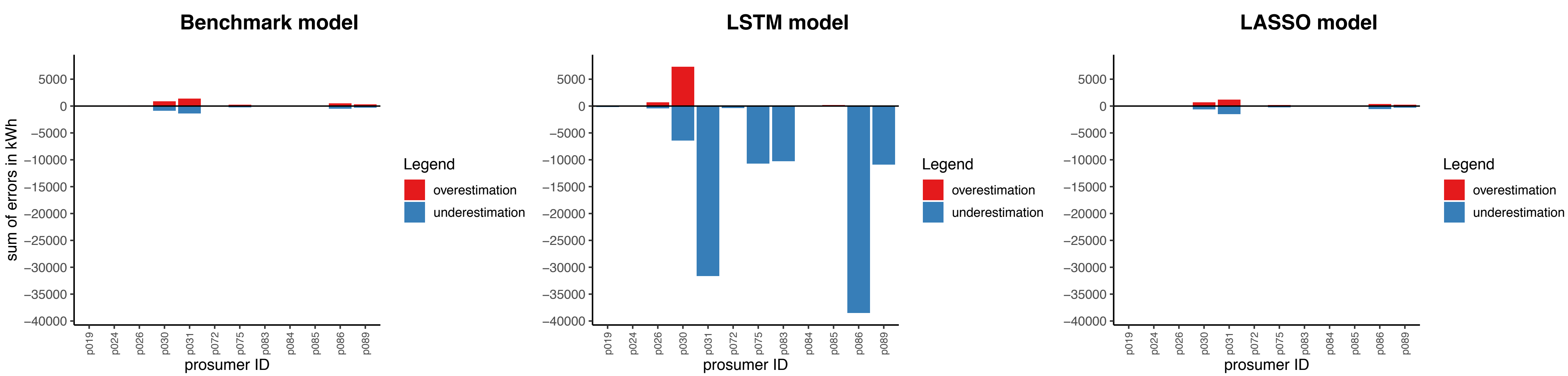
Sum of total over- and underestimation errors by LSTM model predicting energy consumption per consumer data set BLEMplotPredErrors

Over-/Underestimation errors of LASSO model on consumption data



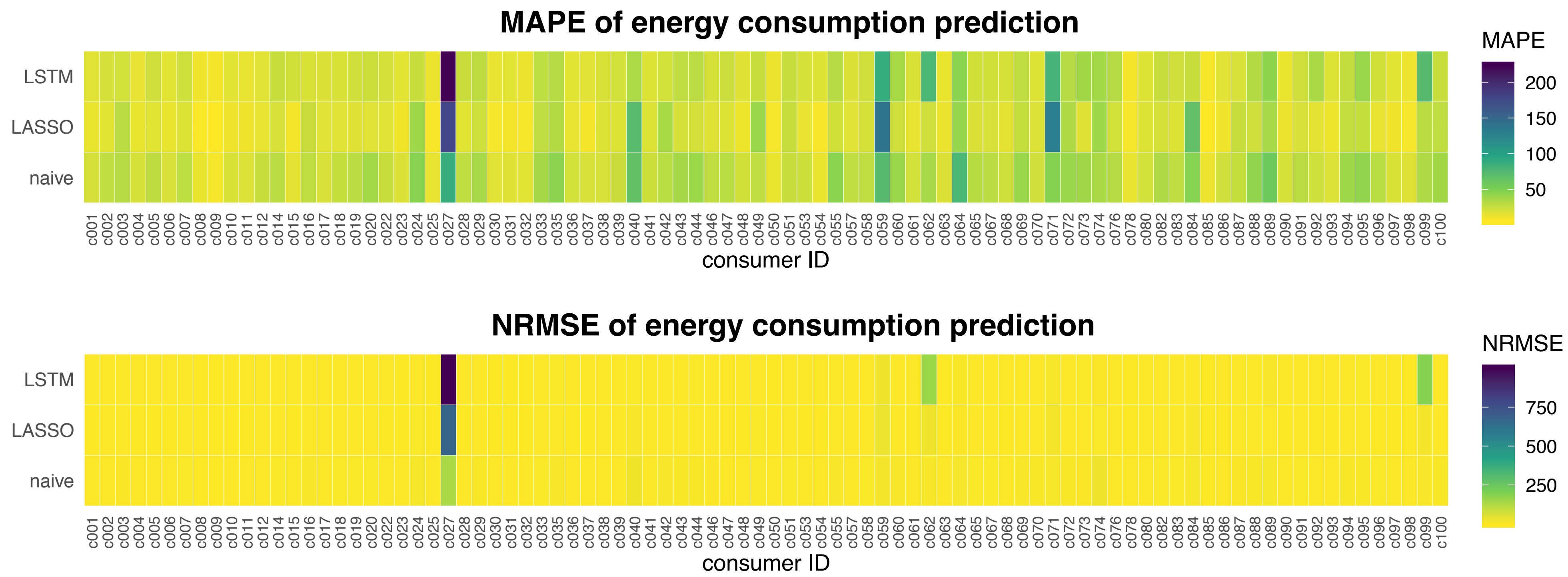
Sum of total over- and underestimation errors by LASSO model predicting energy consumption per consumer dataset. BLEMplotPredErrors

Over- and underestimation errors on production data



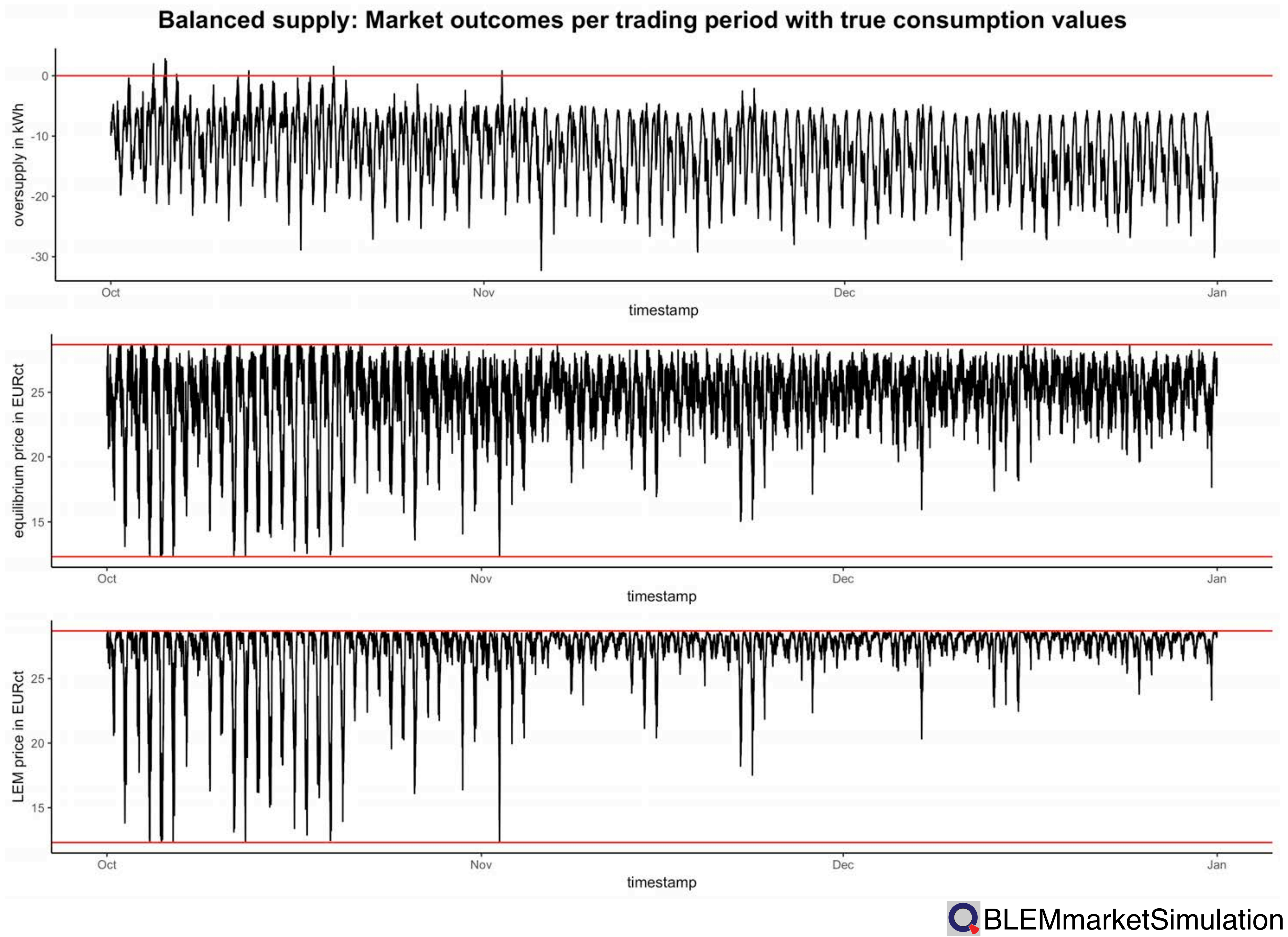
Sum of total over- and underestimation errors by benchmark, LSTM, and LASSO model predicting energy production per production data set. BLEMpSePredErrors

Effect of outliers on relative error measures

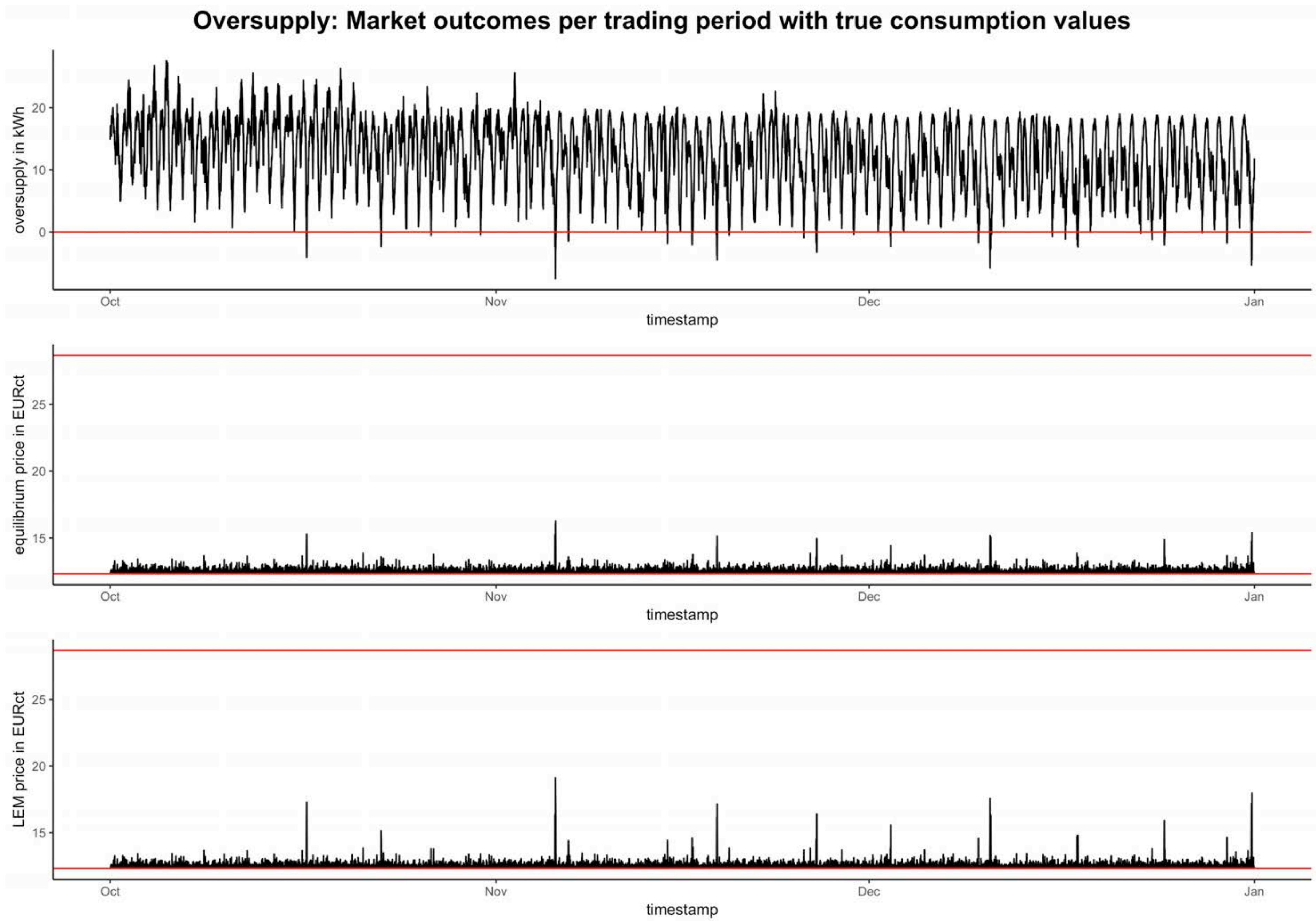


Mean absolute percentage error and normalised root mean squared error for each prediction method on each consumer data set BLEMevaluateEnergyPreds

Outcomes of market simulation in balanced supply scenario

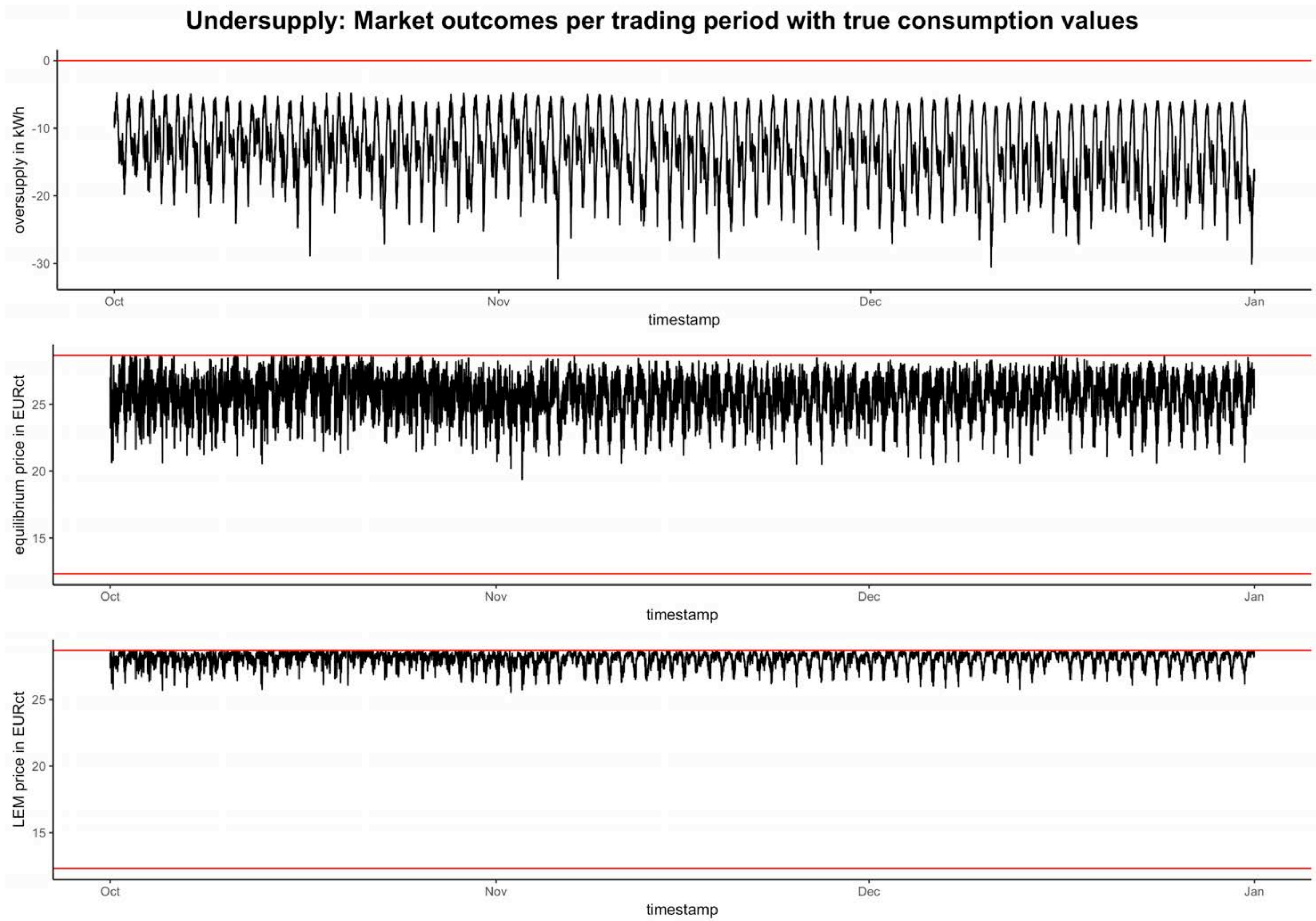


Outcomes of market simulation in oversupply scenario



BLEMmarketSimulation

Outcomes of market simulation in undersupply scenario



BLEMmarketSimulation