Methodologies to Determine IRU Eligibility Price Cap

Day-Ahead Market Enhancements

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Acronyms

CAISO	California Independent System Operator
DAME	Day-Ahead Market Enhancements
DAME	Day-Ahead Market
DLAP	Default Load Aggregation Point
FMM	Fifteen Minute Market
IRU	Imbalance Reserve Up
LMP	Locational Marginal Price
MW	Megawatt
MWh	Megawatt-hour
OLSR	Ordinary Least Squares
P	Percentile
QR	Quantile Regression
RCU	Reliability Capacity Up
RTM	Real-time market
RTPD	Real Time Pre-Dispatch

Executive Summary

As part of the CAISO's Day-Ahead Market Enhancements (DAME) stakeholder initiative, the CAISO has assessed various methodologies that could be used to calculate the imbalance reserve up (IRU) eligibility price cap for the real-time market. This analysis explores the use of regression methodologies with different sets of predictor variables to produce a real-time price cap.

The CAISO highlights the following findings within this analysis.

- **Natural gas commodity prices are a better variable (regressor) for an IRU eligibility price cap than net load data.** When exploring the performance of next-day natural gas commodity prices or CAISO net load data in the context of a quantile regression based on historical fifteen-minute market prices, the natural gas prices often provided a more accurate estimation of real-time energy prices based on a counterfactual analysis over the study period of January through June 2022. This finding holds for the incremental summer months of July through September 2022 as well.

- **The 90th quantile provides a more stable IRU eligibility price cap than the 97.5th quantile.** The effect of different quantiles were assessed and a higher quantile utilized in a quantile regression will naturally pick up higher outliers when estimating the dependent variable. This analysis showed that the IRU eligibility price cap was often overestimated with methodologies that used a higher quantile, *i.e.* the 97.5th quantile, because it included high price outliers that were not representative of actual price conditions. Using a lower quantile, e.g. the 90th quantile, mitigates for the skewness introduced when high outliers largely compose the data sample identified by the chosen quantile used in the regression.

- **The recommended IRU eligibility price calculation methodology accounts for 95 to 99 percent of fifteen-minute market prices in historical tests.** The recommended methodology, or using a quantile regression with the 90th quantile scaled up by a configurable factor (e.g. 1.2), a 60/60 lookback period, and gas prices as the predictor variable, was able to produce real-time IRU eligibility price caps that covered historical fifteen-minute market prices between 95 to 99 percent of the time during the study period of January through June 2022. This indicates that the recommended methodology will be able to produce price caps that estimate or overestimate upcoming fifteen-minute market prices.

- **Using a daily IRU eligibility price cap may eliminate some variability that is present when using a more granular hourly IRU eligibility price cap curve.** Most methodologies presented in this analysis are designed to produce an hourly real-time IRU eligibility price curve, i.e. one distinct $/MWh value for each hour within the trading day. However, utilizing a single $/MWh value that is applicable for the entire trading day provided incrementally better coverage over hourly methodologies.

- **Classification of historical data between weekends and weekdays for used in the regressions did not provide any significant improvement.** The CAISO considered methodologies that distinguished between weekdays and weekends for regressions with natural gas prices as the input. These methodologies provided less coverage than their non-classification counterparts without significant improvement in other metrics. This may be driven by the fact that next-day natural gas prices trade on Friday for the period Saturday through Monday[1] and are static throughout the weekend, while FMM prices are generated daily.

- **Linear regressions performed better than non-linear quadratic regressions for the same set of regressors and input variables.** Two methodologies were tested with a quadratic regression formulation and in both cases, there were extreme outliers of the projected IRU eligibility price cap when compared to the companion methodologies that used the linear formulation. There was some reduction of outliers when the quantile was reduced (i.e. 90^{th} instead of 97.5^{th}) but outliers were still many factors higher than the outliers present when a linear formula was used. Generally, a linear formulation introduced more stability and consistency in the IRU eligibility price cap projection thus was favored for most methodologies tested.

- **Additional analysis performed for the summer 2022 months supports the findings derived from data from previous months.** Applying a 90^{th} quantile linear regression using natural gas prices continued to yield sufficient coverage and scale metrics for the summer 2022 months. Including both CAISO net load and natural gas prices as input predictor variables in the regression performed similarly but saw low or negative difference metrics in September 2022, indicating the projected cap was underestimated compared to the actual FMM price.

[1] For typical weekdays/weekends; trading schedules may be different around trading holidays.

1. Introduction

Within the Day-Ahead Market Enhancements (DAME) stakeholder initiative[2], the CAISO has proposed a day-ahead imbalance reserve product to address real-time ramping differences not covered by hourly day-ahead schedules and to cover net load forecast uncertainty between the day-ahead and real-time markets. The DAME policy has identified a need for a methodology to establish an eligibility criteria for imbalance reserve up awards based on a resource's energy offer price through a calculated hourly eligibility price cap.

The CAISO has previously referred to this real-time cap as the "P97.5 price" as it was initially intended to capture the expected system marginal price if the 97.5th percentile of upward net load forecast uncertainty materialized. However, a different approach has been explored as detailed in this analysis, thus the price cap will be referred to as the imbalance reserve up (IRU) eligibility price cap.

The IRU eligibility price cap would be published in advance of the day-ahead market close in order to give Scheduling Coordinators sufficient time to incorporate the IRU eligibility price cap into their day-ahead bids. Therefore, the IRU eligibility price cap must be derived from data that is available prior to day-ahead market close. The CAISO analyzed the relationship between various predictor variables, including net load and natural gas commodity prices, and historical FMM prices to identify which approach would give an appropriate price projection. This report details the analyses explored by the CAISO and proposes a methodology for calculating the IRU eligibility price cap.

Section 2 describes the quantile regression methodology and the factors considered within variations of methodologies tested. Section 3 compares the performance, efficacy, and limitations of the tested methodologies using four metrics: coverage, difference, closeness, and scale. The appendix contains numerical and graphical results for all methodologies tested.

[2] https://stakeholdercenter.caiso.com/StakeholderInitiatives/Day-ahead-market-enhancements

2. IRU Eligibility Price Cap Calculation Methodologies

Depending on the methodology, the IRU eligibility price cap will provide a $/MWh price cap value for each day or hour in the real-time market. Real-time energy prices are impacted by a variety of factors, including but not limited to: level of demand, generation from variable energy resources and hydroelectric resources, available capacity, operator actions, system conditions, and natural gas commodity prices.

As an alternative to the regression methodology, the CAISO considered using the most recently available DAM supply bid stack available to find a "strike price" that could meet the 97.5th percentile of upward net load uncertainty.[3] However, this approach would require waiting for the closing of the day-ahead market to have all the supply and demand information available, but the price cap needs to be known before the day-ahead market is closed for participants to bid accordingly in the day-ahead market.

The CAISO identified historical net load values and natural gas commodity prices as strong predictors for a single variable regression to forecast fifteen-minute market (FMM) locational marginal prices (LMPs). Net load forecasts and natural gas commodity prices for the upcoming trade date are available before the day-ahead market closes and thus are suitable to calculate the IRU eligibility price cap for the upcoming trade date.[4] The following sections present an in-depth description of the regression methodologies considered to calculate the IRU eligibility price cap.

Regression Formulas

Linear regression is a method to model the relationship between a dependent variable (e.g. FMM prices) and one or more independent variables (e.g. net load values, natural gas prices). Here it is used to fit a model to historical data, which can be used to predict future responses to the dependent variables. The standard linear regression model is ordinary least squares regression (OLSR). This estimates the mean of the dependent variable given the independent variable. In contrast, the quantile regression model estimates quantiles of the dependent variable conditional on the independent variable. Using a higher quantile predicts values that are expected to be greater than the corresponding percent of data.

The linear quantile regression model equation for a single variable is:

$$Q_{Y\,|\,X}(\tau) = a_0 + a_1 \cdot X$$

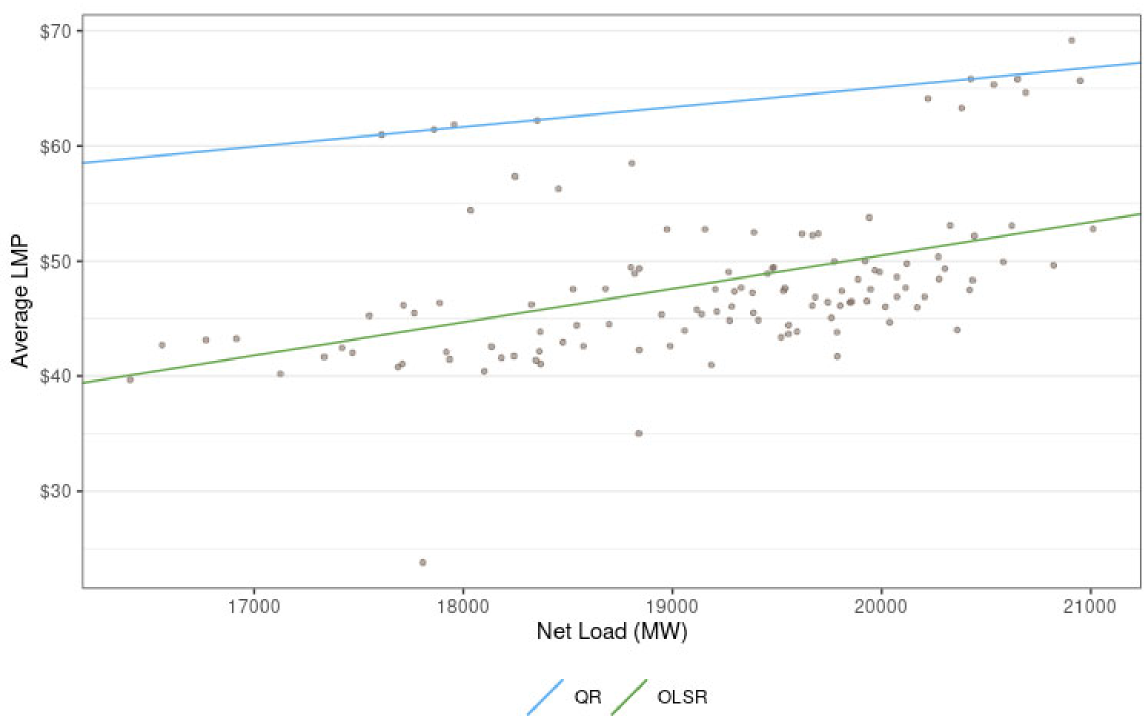
[3] http://www.caiso.com/Documents/Day-AheadMarketEnhancements-Presentation-May13_2022.pdf

[4] Generally, for the day-ahead market, the CAISO uses volume-weighted average commodity hub prices from the Intercontinental Exchange (ICE) obtained between 8 AM – 9 AM Pacific Time. More details on how the CAISO uses natural gas prices in the existing day-ahead market processes can be found in the BPM for Market Instruments, Attachment C.

where Y is the dependent variable, X is the independent variable, a_0 and a_1 are coefficients derived in the regression, and $Q_{Y\mid X}(\tau)$ is the τ-th conditional quantile of Y given X (equivalently, the τ $-th$ quantile of the conditional probability distribution of Y given X).

Figure 1 below shows net load and average FMM prices for trade hour 1 during the month of January 2022. The blue line represents the quantile regression (QR) model for the 97.5th quantile, and the green line represents the OLSR model. The quantile regression fits to the 97.5th quantile of the data and as such provides predicted values greater than a much larger subset of the data than the OLSR line. THE OLSR model is less influenced by higher values because it is fitting to the average of the data.

Figure 1: Quantile vs ordinary least squares regression, sample hour from January 2022



The quantile regressions explored in this analysis were performed at the 97.5th and 90th quantile depending on the methodology. The 97.5th quantile typically accounts for almost all FMM prices in the sample data set except for the highest outliers. Since the 97.5th quantile is highly sensitive to extremes, the 90th quantile was considered as an alternative to eliminate some sensitivity. In order to ensure the 90th quantile provided a reasonable output, post-regression treatments were considered, such as scaling the projected price cap up by a configurable scaling factor.

Another approach to reducing the effect of outliers on the regression was to filter out higher prices, *e.g.* LMPs near or above $1,000/MWh, from the historical data set before it was consumed in the regression. However, the approach of filtering large outliers may undermine the purpose of a quantile regression and a similar effect can be achieved by using a lower quantile.

Linear formulas with one or two predictor variables were considered. Similar to the single variable equation discussed above, the equation for a linear quantile regression using two predictors is:

$$Q_{Y \mid X_1, X_2}(\tau) = a_0 + a_1 \cdot X_1 + a_2 \cdot X_2,$$

where Y is the dependent variable, X_1 and X_2 are the independent variables, $Q_{Y \mid X_1, X_2}(\tau)$ represents the $\tau - th$ conditional quantile of Y given X_1 and X_2, and a_0, a_1 and a_2 are coefficients derived in the regression. Additionally, quadratic formulas were considered for the regression for a few tested methodologies.

Sampling Schemes

A sampling scheme defines what data will be used for an analysis and how it will be chosen. For the sampling scheme of this analysis, FMM LMPs, RTPD net load, and next-day commodity natural gas prices from the PG&E and SoCal Citygate hubs were collected for the period January 1, 2021 through June 30, 2022. The parameters considered for the regression input were the feature type, data granularity, lookback period, and weekday-weekend distinction.

Feature type

The simple average of FMM LMPs across the four default load aggregation points (DLAPs) within the CAISO balancing authority area was compared against three different feature types: RTPD net load, SoCal Citygate next-day commodity gas price, and the simple average of SoCal Citygate next-day and PG&E Citygate next-day commodity gas prices.

Data granularity

Across the different methodologies, the regressions were performed using input data either at fifteen-minute granularity or at hourly granularity (i.e. averaging fifteen minute data across each hour). The advantage of training the model on data with fifteen-minute granularity is that the regression is able to capture the full range of energy prices in each FMM interval within the hour. However, the model is more sensitive to price variations across intervals.

Lookback period

The lookback period is the period of days over which data was sampled for each methodology. A longer lookback period may incorporate seasonal and weather conditions that are not representative of the upcoming trade date (e.g. using summer data for a winter trade date). A shorter lookback period may align better with current weather conditions but may not provide a robust sample for the regression.

This analysis explored a variety of lookback periods, including the use of the previous 45 calendar days, the previous 60 calendar days, and the previous 90 calendar days. Other lookback periods included using historical data anchored from one year prior to the current trading date. For example, one lookback period includes the previous 30 calendar days and 30 calendar days forward from the previous year. Lookback periods of 45 backwards/forwards calendar days and 60 backwards/forwards calendar days were also considered. For brevity, lookback periods will be referred to in the form *a/b* where *a* is the number of days backward and *b* is the number of days forward from the previous year (e.g. 30/0, 45/45, etc.).[5]

Weekend-weekday distinction

Various forecasting methods may distinguish between weekdays and weekends in their formulations. The argument for incorporating a similar approach for the IRU eligibility price cap is that the difference in demand curves between non-weekend and weekend days can be reflected in real-time energy prices. This distinction is intrinsically present in net load data. Natural gas prices are not traded on weekends, and may not accurately reflect the changes in weekend prices. This distinction can be incorporated in the regression in two ways: selecting a sample that reflects the day of the trade date, or adding it as a feature in the regression. The former is not optimal because relying on previous weekend data to project prices for a weekend date restricts the amount of sampling data that remains relevant to the current weather conditions. The latter is feasible and tested in methodologies with natural gas prices as an input. One limitation of this approach is that the natural gas price traded for the weekend days also applies to the Monday trade date.

[5] For example, say that the 30/30 methodology is being used to calculate the price cap for trading day August 31, 2022; the regression would consider data from 30 days backwards, i.e. August 1 through August 30, 2022, as well as 30 days forwards from the previous year, i.e. August 31 through September 29, 2021.

3. Performance of IRU Eligibility Price Cap Methodologies

For each methodology, the CAISO used the quantile regression model to project an IRU eligibility price cap for all hours for trade dates January 1, 2022 through June 31, 2022. The performance of the projected price caps was analyzed against actual, realized FMM prices for each trade date and hour. An incremental analysis was performed for July 1, 2022 through September 30, 2022 to analyze the performance of a handful of top-performing methodologies during summer 2022 conditions. The CAISO used the following four metrics to analyze the efficacy of the methodologies and to quantify the relationship between the projected price caps and actual FMM prices:

1. Coverage: percentage of time that the projected price cap was sufficient to cover, *i.e.*, was greater than or equal to, the actual FMM price.
2. Difference: the difference between the projected price cap and the actual FMM price. Positive difference indicates that the projected price cap covers the actual FMM price.
3. Closeness: the absolute difference between the projected price cap and the actual FMM price.
4. Scale: the ratio of the actual FMM price to the projected price cap. A scale value less than one indicates that the projected price cap covers the actual FMM price.

Overall Assessment of Methodologies

This section provides an overview and assessment of the results from the different methodologies tested. The results support the use of a quantile regression methodology that uses the following features:

- 60/60 lookback period[6]
- Historical average gas prices as the predictor variable
- Linear quantile regression at the 90^{th} quantile
- Configurable scaling factor of 1.2

Table 1 below describes all methodologies referenced in this report. In the notation below, ‘Average Gas’ represents the average of SoCal and PG&E Citygate prices and ‘Weekend distinction’ represents when weekends were distinguished from weekdays in the methodology. Please refer to the appendix for summary statistics and additional details on the results of all tested methodologies.

[6] 60 days of historical data before the trade date and 60 days of historical data forward from the trade date, from the previous year.

Table 1. Regression Methodology Overview

No.	Features	Formula	Quantile	Lookback Period	Data Granularity	Additions
1	Average Gas	Linear	97.5	30/30	Fifteen minute	--
2	Average Gas	Linear	97.5	45/45	Fifteen minute	--
3	Average Gas	Linear	97.5	60/60	Fifteen minute	--
4	Average Gas	Linear	97.5	45/0	Fifteen minute	--
5	Average Gas	Linear	97.5	60/0	Fifteen minute	--
6	Average Gas	Linear	97.5	90/0	Fifteen minute	--
7	Average Gas	Linear	90	30/30	Fifteen minute	--
8	Average Gas	Linear	90	30/30	Fifteen minute	1.1 scalar
9	Average Gas	Linear	90	30/30	Fifteen minute	1.2 scalar
10	Average Gas	Linear	90	60/60	Fifteen minute	--
11	Average Gas	Linear	90	60/60	Fifteen minute	1.2 scalar
12	Average Gas	Linear	97.5	60/60	Hour	--
13	Average Gas	Linear	97.5	60/60	Hour	Weekend distinction
14	Average Gas	Linear	90	60/60	Hour	--
15	Average Gas	Linear	90	60/60	Hour	1.2 scalar
16	Average Gas	Linear	90	60/60	Hour	Weekend distinction
17	Average Gas	Quadratic	97.5	60/60	Fifteen minute	--
18	Average Gas	Quadratic	90	60/60	Fifteen minute	--
19	Average Gas	Linear	90	60/60	Fifteen minute	Daily cap, 1.2 scalar
20	SoCal Gas	Linear	97.5	30/30	Fifteen minute	--
21	SoCal Gas	Linear	97.5	60/60	Fifteen minute	--
22	SoCal Gas	Linear	90	60/60	Fifteen minute	--
23	Net Load	Linear	97.5	30/30	Fifteen minute	--
24	Net Load	Linear	97.5	60/60	Fifteen minute	--
25	Net Load	Linear	90	60/60	Fifteen minute	--
26	Average Gas, Net Load	Linear	97.5	30/30	Fifteen minute	--
27	Average Gas, Net Load	Linear	97.5	60/60	Fifteen minute	--
28	Average Gas, Net Load	Linear	90	60/60	Fifteen minute	--
29	Average Gas, Net Load	Linear	90	60/60	Fifteen minute	1.2 scalar
30	Average Gas, Net Load	Linear	97.5	60/60	Hour	--

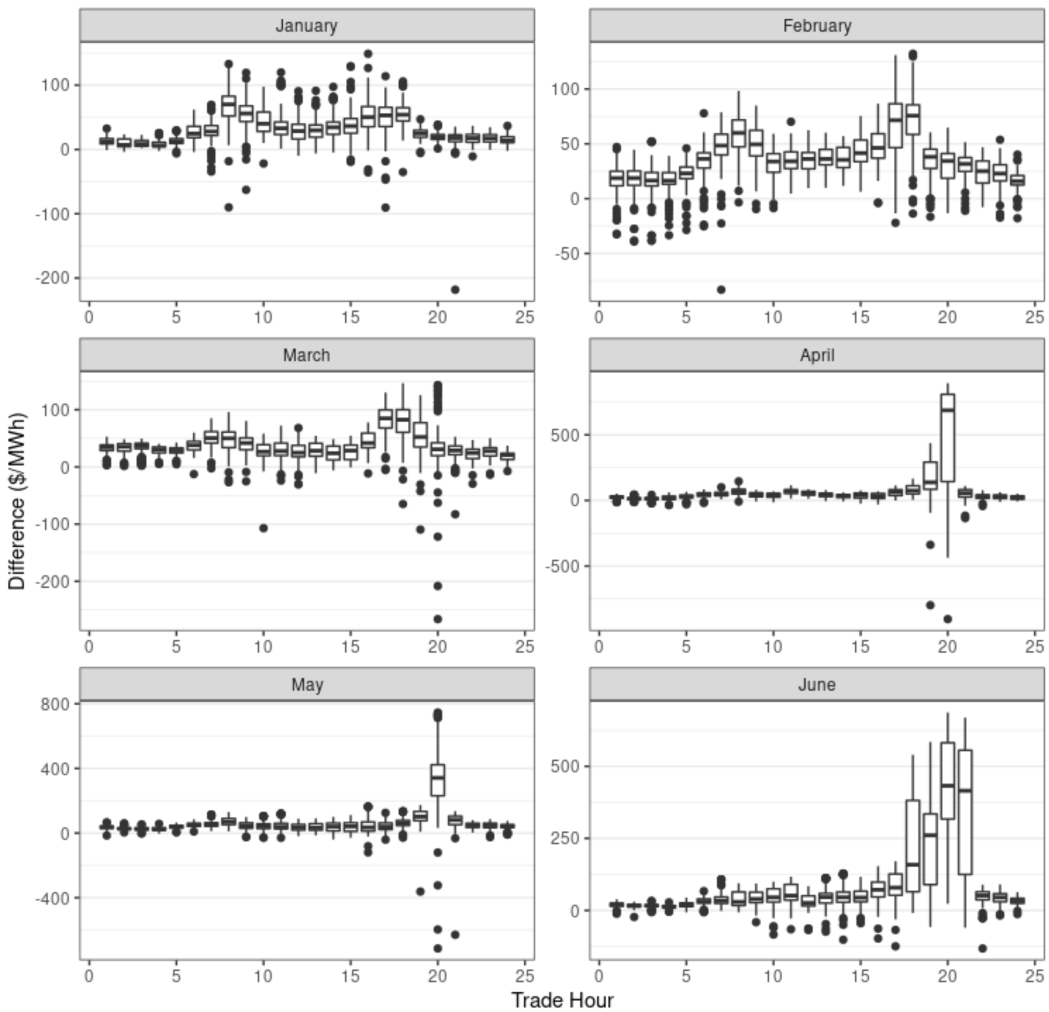
<u>Testing various lookback periods</u>

The CAISO compared how different lookback periods affected results of quantile regressions with average PG&E and SoCal Citygate commodity gas prices as inputs and with fifteen-minute granularity (i.*e.,* gas prices were copied over to each fifteen-minute interval to align with the other regression component).

The first three methodologies used a linear quantile regression at the 97.5th quantile with similar lookback periods, 30/30, 45/45, and 60/60. Each of the methodologies performed similarly with coverage between

96 to 97 percent, closeness ranging from $30 to $87/MWh, and scale ranging from 0.49 to 0.66[7]. In general, higher coverage yielded lower closeness and scale values. Figure 2 shows the hourly boxplot of difference by month for methodology 1. A large upwards deviation from zero in the peak hours in April, May, and June can be observed, however this was somewhat diminished in methodologies 2 and 3. Figure 3 shows the hourly boxplot of difference by month for methodology 3 for comparison, and the figure for methodology 2 can be found in the appendix.

Figure 2: Hourly boxplot of difference by month, methodology 1



[7] Methodologies 1 through 3

Figure 3: Hourly boxplot of difference by month, methodology 3

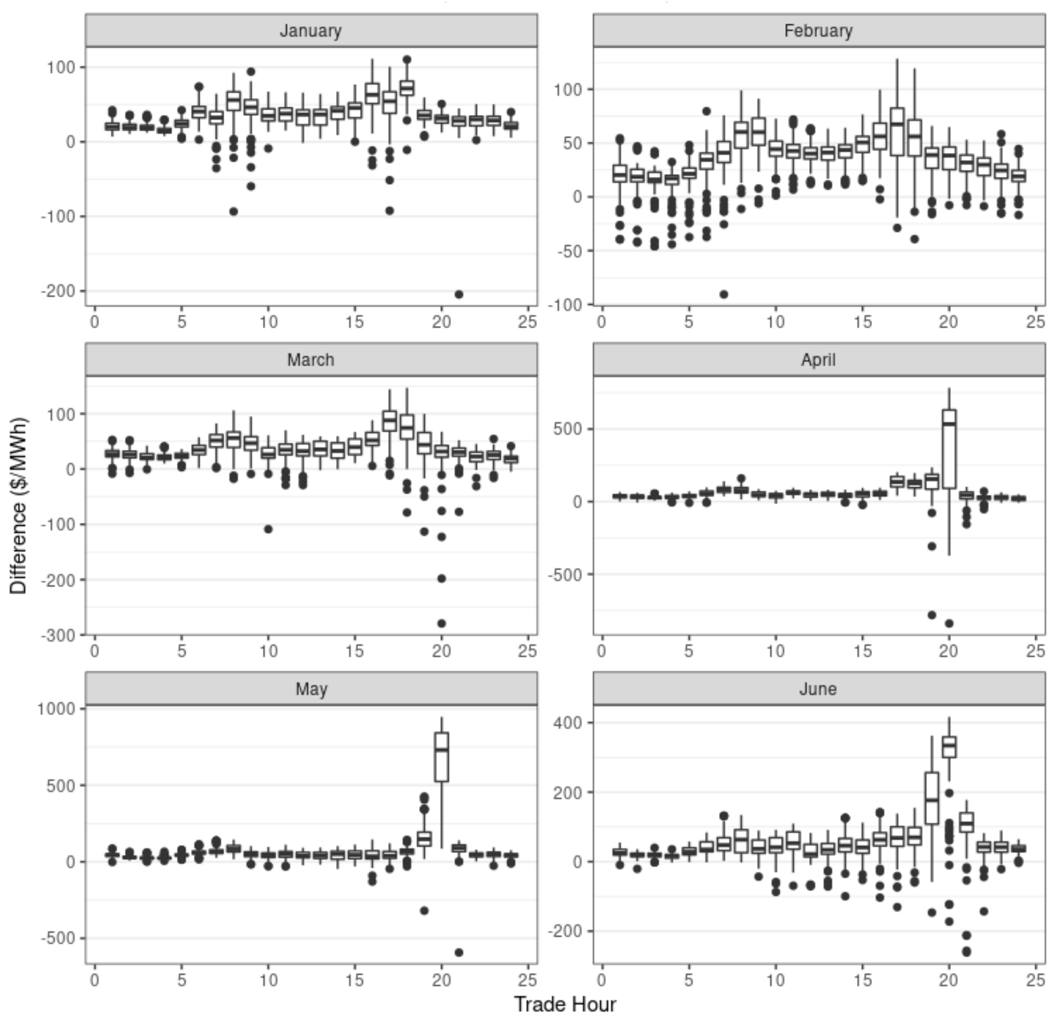
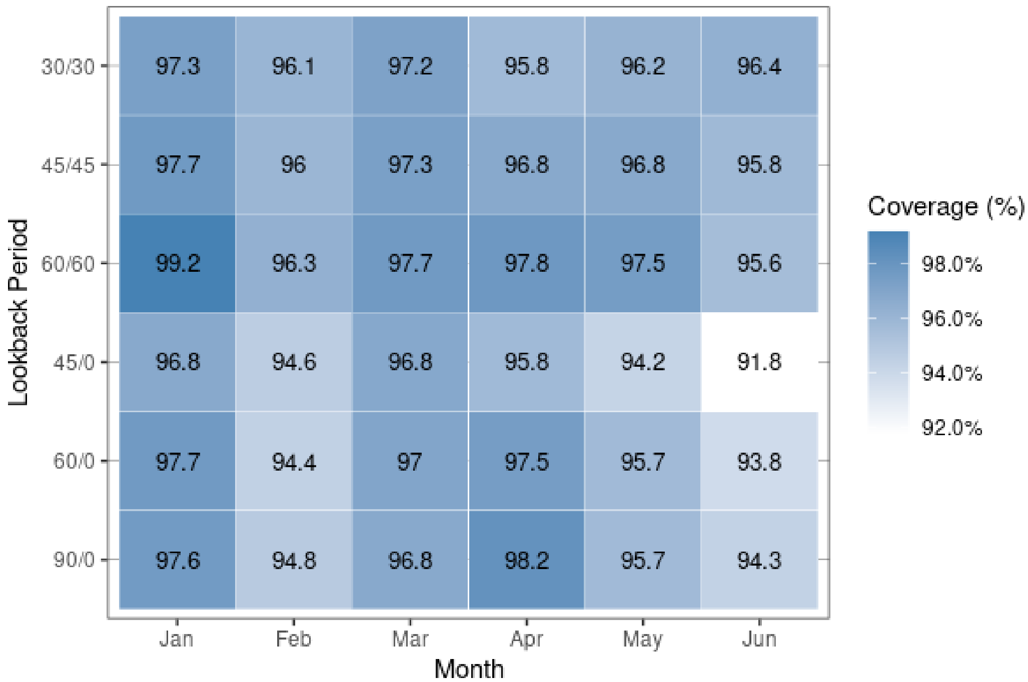


Figure 4 below displays the average monthly coverage results across different lookback periods for methodologies 1 through 6. The purpose of this comparison was to identify whether any lookback period performed particularly well while holding all other features constants. As the figure below shows, the 60/60 and 45/45 lookback periods generally yielded the highest coverage percentages across the six months of the study period. Since the 60/60 lookback period provided a broader sample of historical data than the 45/45 test without sacrificing coverage, the 60/60 period was used for future tests, although some tests were run with the 30/30 period for robustness. Lookback periods with no prior year historical data (*e.g.* 45/0, 60/0, 90/0[8]) exhibit slightly lower coverage than other lookback periods and also saw slightly more deviation in difference than other lookback periods, thus they are not utilized in future tests.

[8] Methodologies 4 through 6

Though not pictured in the figure below, the 60/60 period continues to provide greater coverage and similar or lower scale than the 30/30 period for tests using the 90th quantile, and this trend remains when the price cap is scaled up by a factor of 1.2[9].

Figure 4: Coverage across different lookback periods in methodologies 1 through 6



Testing lookback periods with different predictor variables

The CAISO tested the 60/60 lookback period against the 30/30 lookback period for the 97.5th quantile regressions with other predictor variables, as well. When comparing the results of methodology 20 and 21, which use only the SoCal Citygate commodity gas price as the predictor variable, methodology 21, which uses the 60/60 period, provides better coverage with overall less deviation in difference in peak load hours as compared to methodology 20. This trend persists for regressions with net load as the predictor variable[10]. For methodologies with both the average commodity gas price and the net load as predictor variables, the 60/60 lookback period did not have significant advantages or disadvantages compared to the 30/30 period[11]. Thus, the CAISO determined that the 60/60 lookback period provided the best sample for the regression.

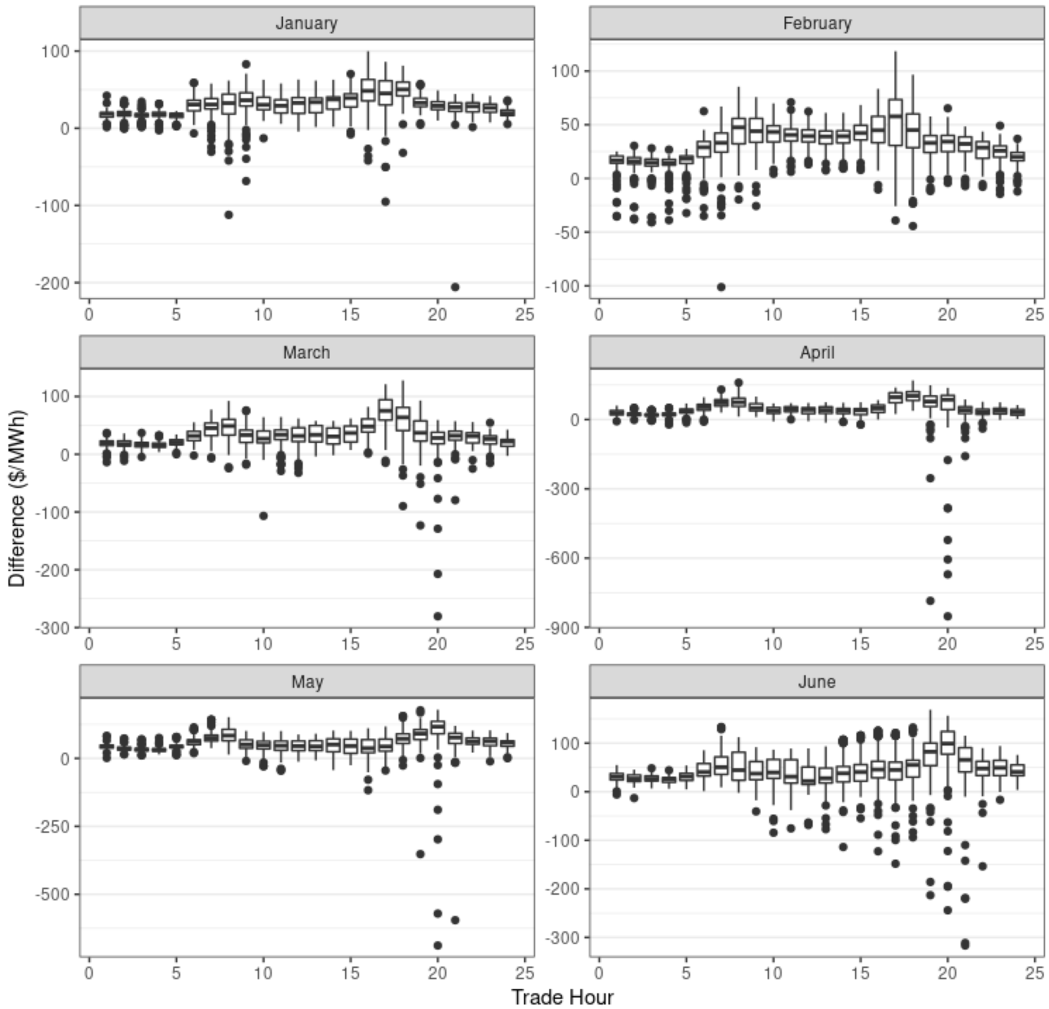
[9] Methodologies 7 through 11
[10] Methodologies 23 and 24
[11] Methodologies 26 and 27

Applying a configurable scalar

The CAISO compared two choices for quantile: the 97.5th quantile and the 90th quantile with an additional scalar applied to the calculated price cap. An iterative analysis was performed on scalars of different numerical values, and a value of 1.2 was selected as an appropriate scalar to increase coverage while balancing closeness when compared to results from the corresponding baseline test that did not have a scalar applied. Using the 90th quantile with a 1.2 scalar allowed the model to be less susceptible to extremes while retaining a similar coverage to the 97.5th quantile methodology[12]. Figure 5 below shows the results of using the 90th quantile with a 1.2 scalar. One consideration of this methodology is that, in both tests with average gas prices as the input and with average gas price and net load as inputs, there remain several large outliers for difference in the negative direction (i.e., the projected price cap was lower than actual FMM prices across the study period). These outliers are mostly attributed to periods where FMM LMPs exceeded $400/MWh.

[12] Methodologies 3, 10, and 11

Figure 5: Hourly boxplot of difference by month, methodology 11



<u>*Outcomes of using single regression feature*</u>

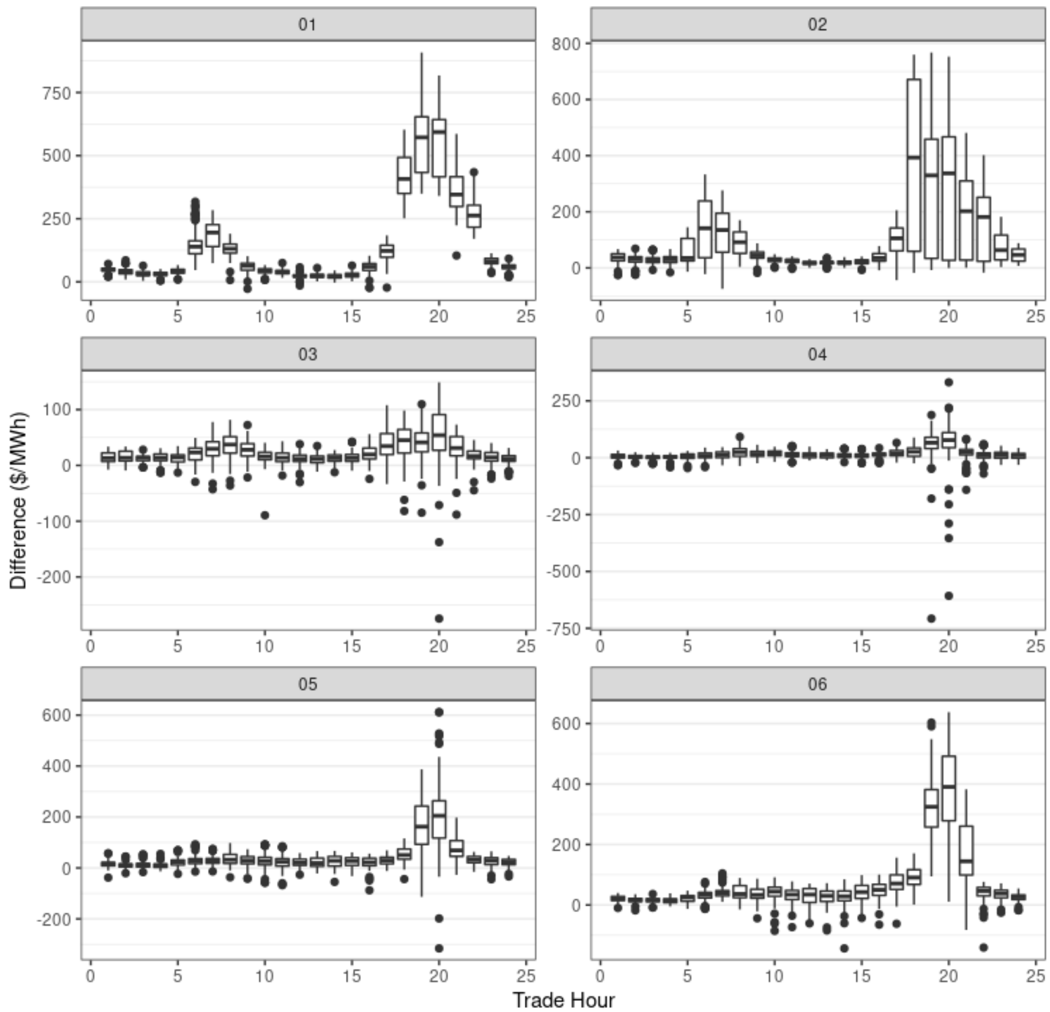
Taking the simple average of PG&E and SoCal Citygate commodity gas prices provided the best results among the feature types considered in tests with a 60/60 lookback period. Using average gas prices had higher coverage than just using the SoCal Citygate gas price for a majority of the months with both the 97.5th and 90th quantile[13].

Tests that used CAISO net load as the predictor variable had difference metrics that were much more sensitive and variable on a monthly basis than tests that used average gas prices. In general, higher coverage metrics were unfavorably complemented with larger closeness and difference metrics. The figure below

[13] Methodologies 3, 10, 21, and 22

highlights the volatility observed in the net load tests. Based on the observed month-over-month volatility from the tests using only net load, the CAISO determined it is not favorable to use only net load as a predictor variable for a single-variable regression. Using the average of PG&E and SoCal Citygate commodity gas prices is favorable over using only net load.

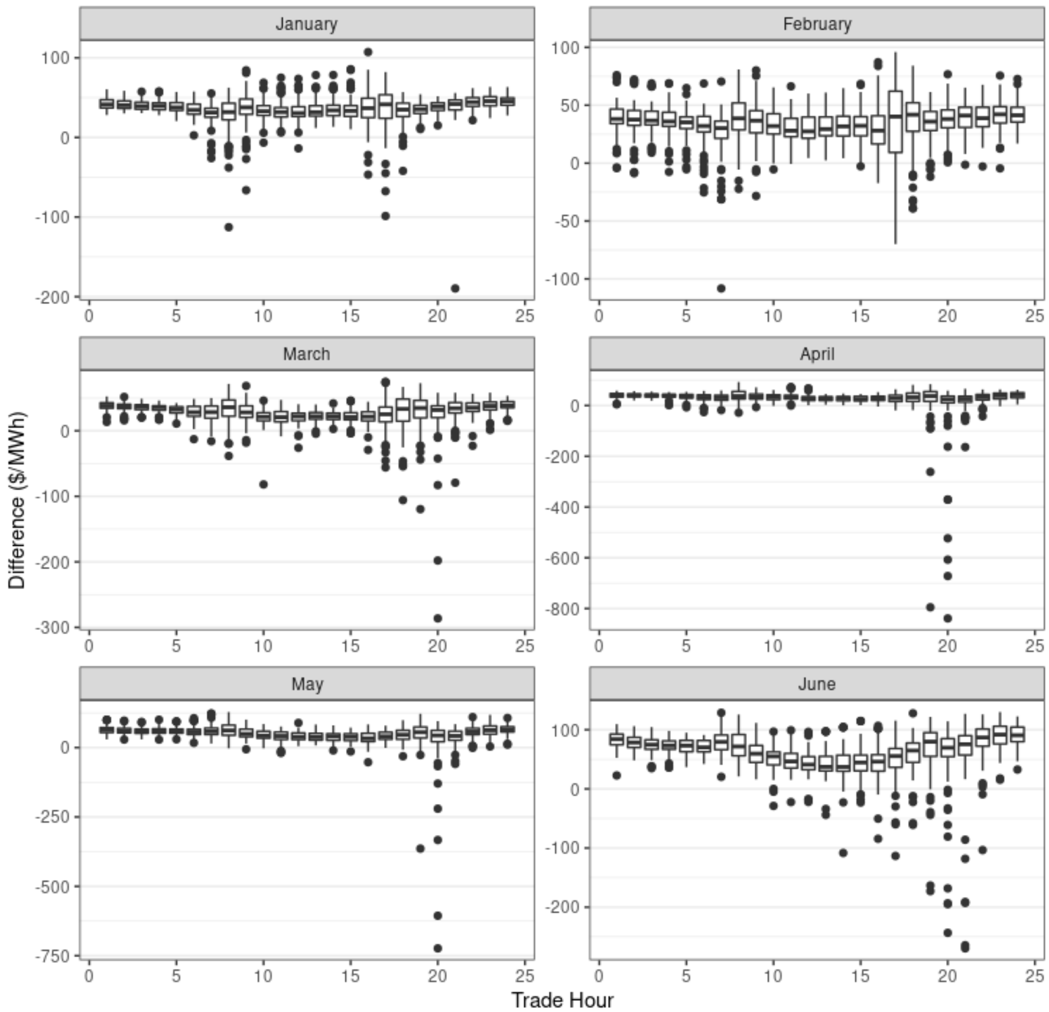
Figure 6: Hourly boxplot of difference by month, methodology 24



Outcomes of using multiple regression features

The CAISO also explored methodologies that use both net load and average gas prices as features within the quantile regression. In general, these methodologies performed similarly or slightly better than tests using only average gas prices, with similar coverage, lower closeness, and a more consistent median hourly average difference across trade hours as shown in Figure 7[14]. The trade-off with using both features in the regression is a greater amount of negative outliers, though this also appears in average gas tests with the 90th quantile[15].

Figure 7: Hourly boxplot of difference by month, methodology 27



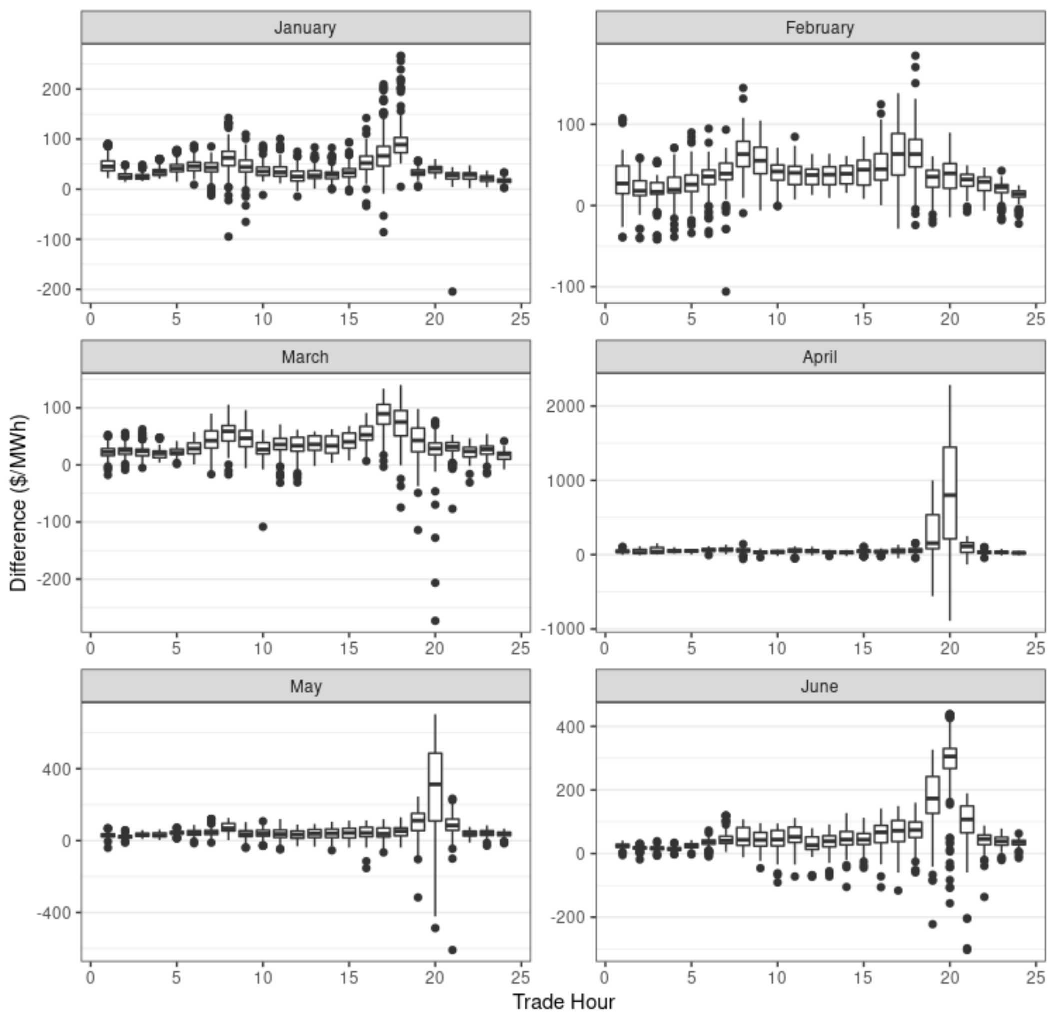
[14] Methodologies 3, 10-11, and 26-28; Figure 7 can be compared with Figure 3 further above to observe the comparison

[15] Methodologies 10-11

Using a quadratic regression formula

Although a majority of methodologies utilized a linear quantile regression formula, two tests were performed using a second order quadratic formula with average gas price as an input to assess whether a quadratic formula would yield more favorable results. Methodology 17 used the 97.5th quantile and though it was comparable to its linear 97.5th quantile counterpart, methodology 3, for most months, there were multiple instances of extreme outliers above $1,000/MWh and even $2,000/MWh in the price caps for April 2022[16]. This can be seen below in Figure 8. These observations are reduced for methodology 18 results which uses the 90th quantile. However, using a linear formula is generally preferred to a quadratic formula in order to avoid instances where the projected price cap may be many factors greater than the actual FMM price due to the nature of the quadratic formulation.

Figure 8: Hourly boxplot of difference by month, methodology 17



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[16] Methodologies 3 and 17

Using historical data at an hourly granularity

Fifteen-minute granularity and hourly granularity were compared for tests with just average gas prices as the input and for tests with both average gas price and net load as inputs. Methodologies with hourly granularity had lower coverage overall without significant benefit in other metrics[17]. This is true for both average gas price and net load inputs. In addition, distinguishing between weekends and weekdays in the data did not provide any significant improvement to results[18].

Daily IRU Eligibility Price Cap

The CAISO also analyzed results when calculating a daily IRU eligibility price cap (*i.e.*, one cap for the entire day instead of 24 distinct caps). The advantage of setting a daily price cap is that it eliminates some of the variability associated with an hourly cap and could increase coverage on an average monthly basis. Further, it provides more simplicity for Scheduling Coordinators who need to react to the price cap when submitting bids.

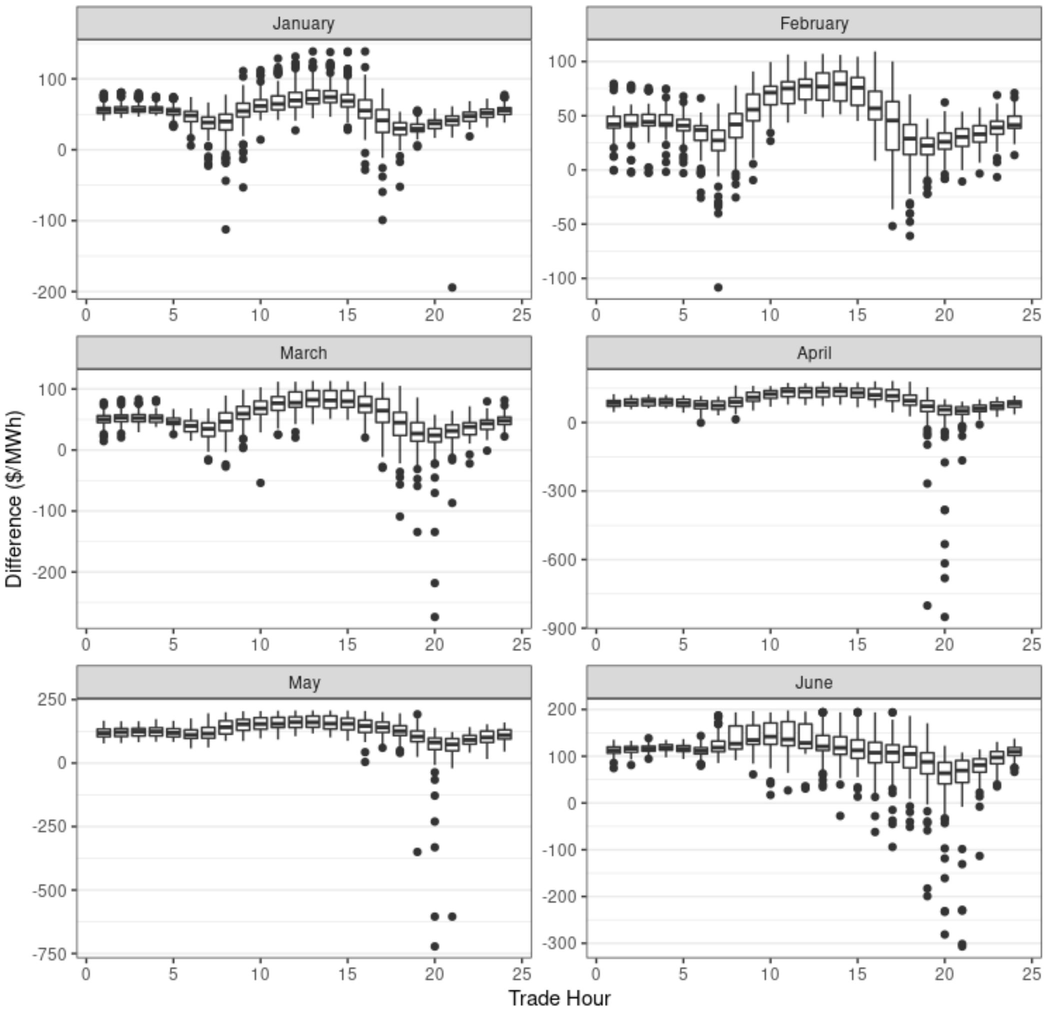
The daily price cap was determined by taking the greatest of the hourly price caps projected in the methodologies discussed above. The figure below shows the results of using a daily cap from a quantile regression of FMM prices against average gas prices at the 90th quantile scaled up by a factor of 1.2[19]. The daily cap provides coverage between 98 and 99 percent and improves between 0.5 percent and 3 percent for each month compared to the hourly cap. The average closeness is much greater, as expected, and averages around $100/MWh for the last three months. The difference follows the inverse shape of FMM prices. The average scale decreases from 51 to 63 percent to 33 to 50 percent using the hourly methodology. Due to the nature of price movement throughout the day, and the methodology used here, the daily cap offers a higher cap value for non-peak hours when prices are generally lower.

[17] Methodologies 3, 10, 12, and 14

[18] Methodologies 12-14 and 16

[19] Methodology 19

Figure 9: Hourly boxplot of difference by month, methodology 19



Summer 2022 Performance

A handful of the methodologies described in the sections above were tested on the summer months of July through September 2022. The intent of expanding the analysis to the summer 2022 months is to examine how the methodologies perform during months that tight supply conditions with elevated prices. The table below shows the regression methodologies that were re-tested to consider data from July through September 2022. The primary aim was to re-test the methodology that performed best during the January through June 2022 timeframe (methodology 11) and also explore the effect from the addition of the configurable scalar value of 1.2 (methodology 10) during the summer 2022 months. Since the multi-variate regression using both average gas and net load also performed well based on previous tests, the two methodologies (28 and 29) were re-tested during the summer 2022 timeframe as well.

Table 2. Regression methodologies tested for July – September 2022

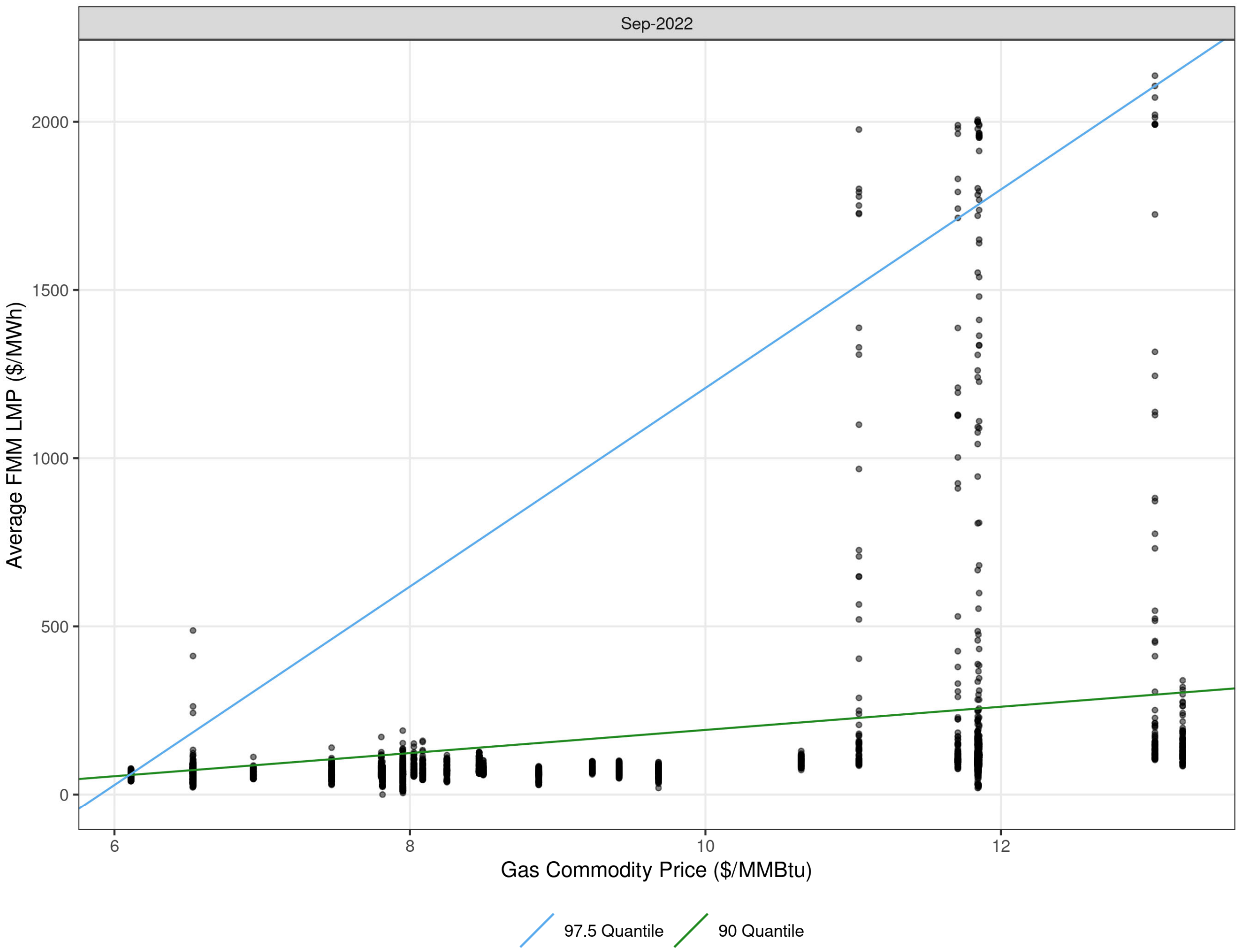
No.	Features	Formula	Quantile	Lookback Period	Data Granularity	Additions
10	Average Gas	Linear	90	60/60	Fifteen minute	--
11	Average Gas	Linear	90	60/60	Fifteen minute	1.2 scalar
28	Average Gas, Net Load	Linear	90	60/60	Fifteen minute	--
29	Average Gas, Net Load	Linear	90	60/60	Fifteen minute	1.2 scalar

Figure 10 below shows natural gas commodity prices plotted against average FMM LMPs within the CAISO area specifically for September 2022. Lines are plotted showing both the 90th and 97.5th quantiles for the dataset. For the month of September, high gas commodity prices were generally correlated with high average FMM LMPs. Because using the 97.5th quantile of data would pull in outliers that may skew the regressions, methodologies using the 90th quantile were chosen for further analysis for the summer months. This choice of quantile is also consistent with findings and recommendations from the previous months of 2022.

As depicted below, FMM LMPs were driven to high values during the heat wave that spanned from approximately September 1st through September 9th, 2022. During this period, the energy bid cap was raised to $2,000/MWh for various trading days and hours in both the day-ahead and real-time markets thus market prices were correspondingly high, especially when compared to prices from the previous summer 2022 months, as well as prices from the same timeframe in September 2021. Naturally, any regression that is run on historical data will incorporate the dynamics of that historical data to some extent.

In general, the four methodologies that were re-tested during the summer 2022 months showed significantly higher difference metrics for the month of September, reaching outlier values between $1,000/MWh - $2,000/MWh. This is due in large part to the interplay between historical data in the regression and actual prices. Just prior to, and at the beginning of the heat event, prices used in the regression were relatively low (both from the past 60 days and from the 60 days forward from the previous year) so a lower price cap was projected but actual LMPs climbed much higher, resulting in a large negative difference. Moving through the heat event period, the regression began to pick up the higher prices from previous days which helped set the price cap closer to actual LMPs. At the end of the heat event period, the regression was still picking up higher prices from previous days even as actual LMPs started to come down, resulting in larger positive difference values. Similarly, future months that use September 2022 as part of the historical dataset in the regression (*i.e.* September 2023) will factor in these higher prices when calculating the price cap which may set the price cap artificially high when compared to actual prices.

Figure 10. Average gas prices vs. average FMM LMPs with quantiles, September 2022



Single variable regression results (methodologies 10 and 11)

Figure 11 below shows a boxplot of difference for the months July through September 2022 for methodology 10 (average gas price, 90th quantile linear regression, 60/60 lookback period). In general, the outlier magnitude of difference for the summer months is greater than the outlier magnitude for the previous months of 2022. The large magnitude is most pronounced during evening peak hours, consistent with previous months. A negative difference value indicates that the actual FMM price, averaged across each of the four intervals within the hour, was greater than the projected price cap value.

Table 3 below shows the coverage, closeness, difference, and scale metrics for the summer 2022 months, averaged across each month. In general, when comparing results for this methodology to the previous months of 2022, average percent coverage decreases throughout the summer while average scale remains relatively consistent. Average closeness jumps in September 2022, primarily driven by the high FMM LMPs that materialized at the beginning of the month due to the heat event. Since closeness is the absolute value of difference, it will be driven higher when compared to difference because of the high magnitude of difference outliers in both the positive and negative directions.

Figure 11: Difference for Methodology 10, summer 2022

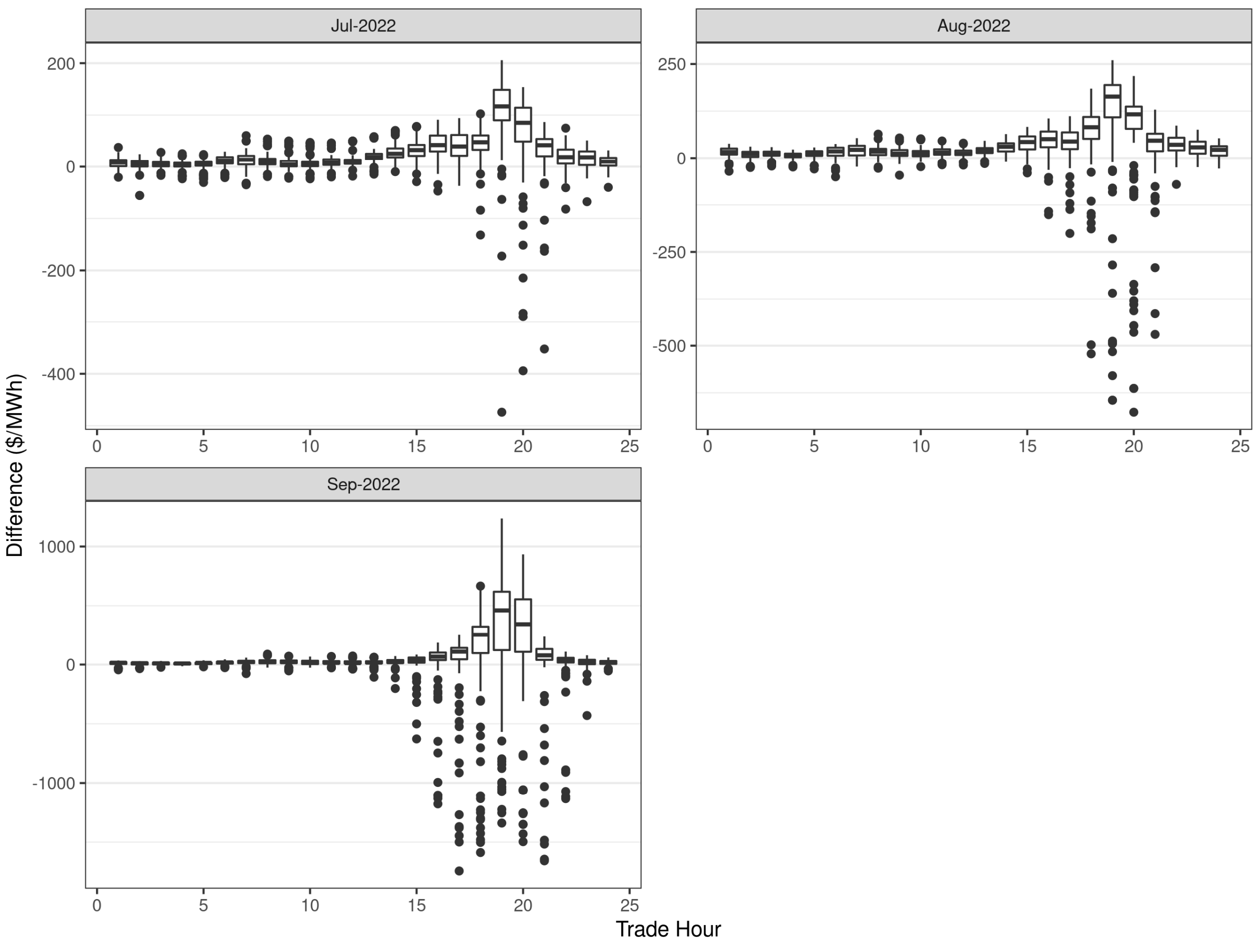


Table 3: Results for Methodology 10, summer 2022

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
July 2022	86.30%	27.29	22.83	0.80
August 2022	88.74%	40.24	27.91	0.81
September 2022	85.52%	104.37	33.56	0.81

Figure 12 below shows a boxplot of difference for the months July through September 2022 for methodology 11 (average gas price, 90^{th} quantile linear regression, 60/60 lookback period, 1.2 scalar). This methodology is identical to the methodology previously discussed above, with a 1.2 scalar applied on the final projected price cap value. Like the previous methodology, the difference boxplots for the summer months show outliers that are greater in magnitude than previous months in 2022.

However, the coverage metric showed improvement between the two methodologies. Coverage, along with other metrics for methodology 11, are shown in Table 4 below. Often, for intervals that were not previously "covered" under methodology 10 in the summer 2022 months, the difference between the projected cap and actual FMM LMP value was relatively small, so adding a 1.2 scalar to the projected cap was sufficient to set the projected cap value higher than the actual FMM LMP, thus improving the coverage metric. Although the coverage metric improved, the average scale decreased for methodology 11 as compared to methodology 10. This indicates that although the projected cap was sufficient to cover the actual FMM LMP, it was often an overestimation of the actual FMM LMP. This is consistent with results from the first six months of the year.

Figure 12: Difference for Methodology 11, summer 2022

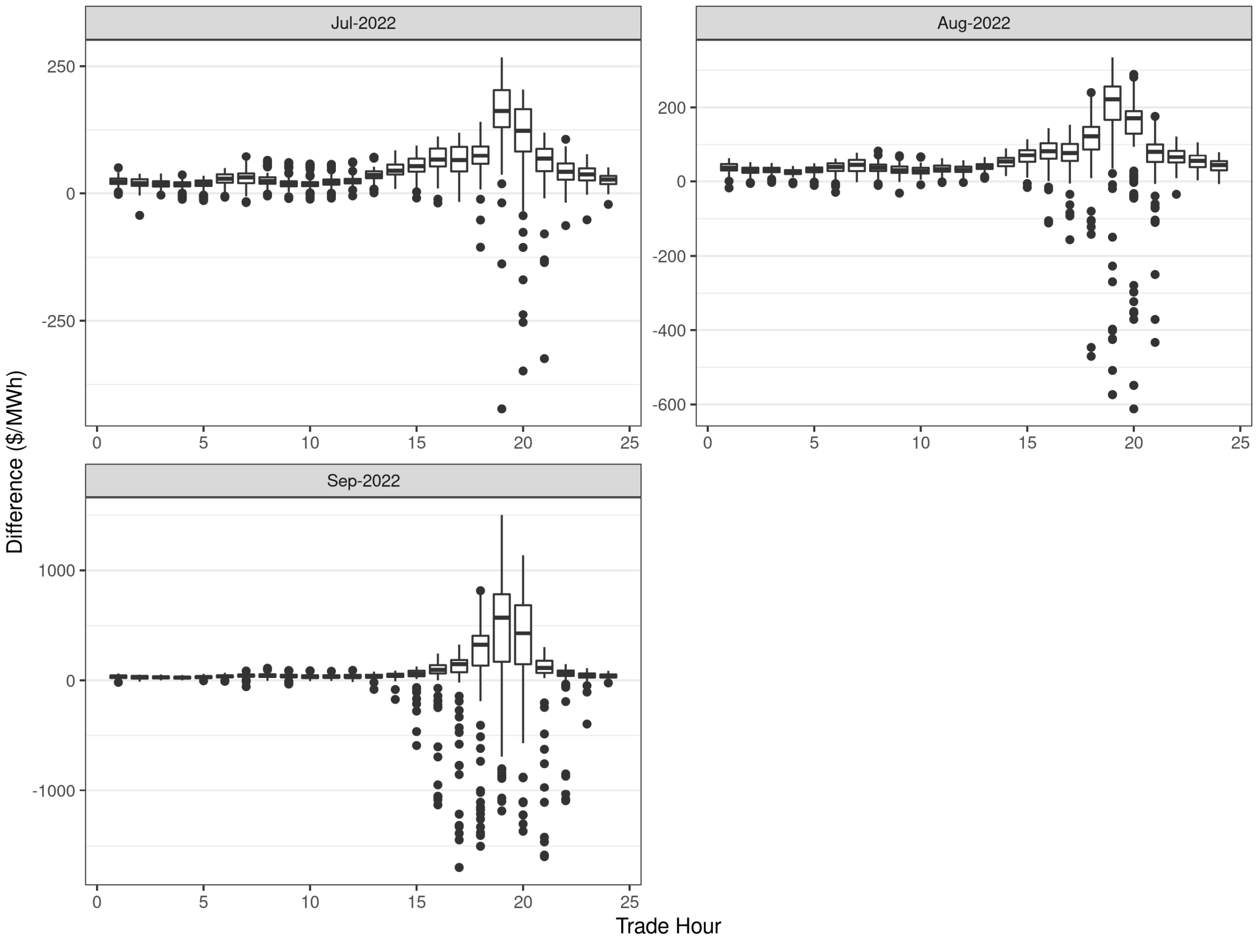


Table 4: Results for Methodology 11, summer 2022

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
July 2022	97.08%	45.13	42.92	0.67
August 2022	97.11%	63.12	54.69	0.67
September 2022	93.64%	127.64	67.72	0.68

<u>Multiple variable regression results (methodologies 28 and 29)</u>

Figure 13 below shows a boxplot of difference for the months July through September 2022 for methodology 28 (average gas price and net load, 90^{th} quantile linear regression, 60/60 lookback period). In general, the outlier magnitude of difference for the summer months is greater than the outlier magnitude for the previous months of 2022. The large magnitude of difference is most pronounced during evening peak hours, consistent with previous months' findings for this methodology. Negative difference value indicates that the projected price cap value is less than the actual FMM price (averaged across each of the four intervals within the hour).

Table 5 below shows the analysis metrics for July through September 2022 for methodology 28. In general, when compared to metrics for the beginning of 2022, coverage remains consistent while closeness is greater in September than previous months. The average difference is negative for September, indicating a significant number of instances where the actual FMM price was higher than the projected cap. This is due in part to the high pricing between $1,000/MWh and $2,000/MWh that materialized during the September heat event.

Figure 13: Difference for Methodology 28, summer 2022

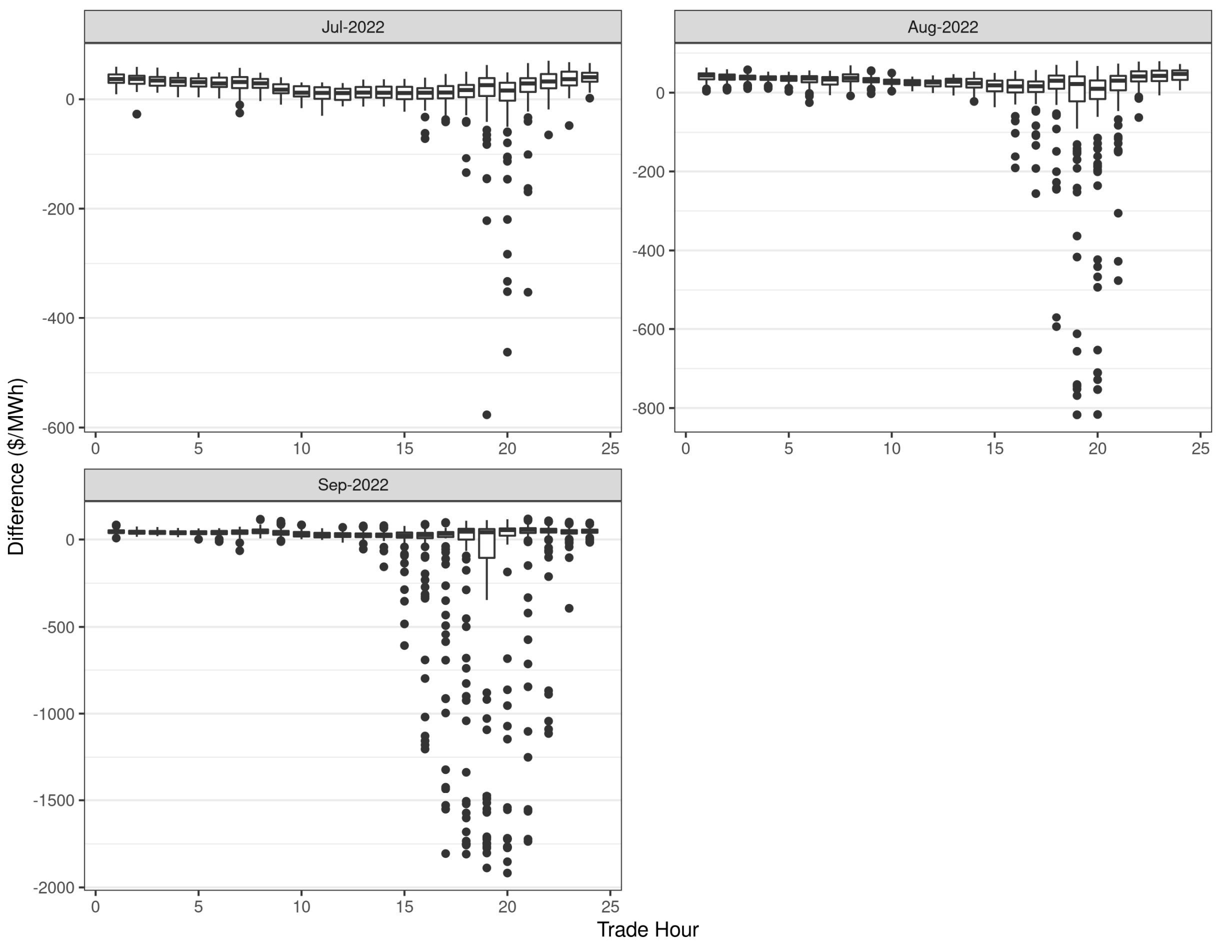


Table 5: Results for Methodology 28, summer 2022

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
July 2022	88.76%	26.33	21.16	0.78
August 2022	91.21%	38.80	21.16	0.81
September 2022	91.66%	86.25	-11.50	0.91

Figure 14 below shows a boxplot of difference for the months July through September 2022 for methodology 29 (average gas price and net load, 90^{th} quantile linear regression, 60/60 lookback period, 1.2 scalar). Consistent with results for methodology 28 shown above, the difference outliers for the summer months have a higher magnitude than compared to previous months.

Similar to the comparison between methodology 11 and 12, the addition of the 1.2 scalar improved the coverage metric but resulted in a lower average scale metric. These results are shown below in Table 6. This trend was consistent between methodologies 28 and 29 for the previous months of 2022 as well. The closeness metric also increases in September 2022 compared to the other summer months. Since closeness is an absolute value of difference, this higher magnitude value is driven by the large negative outliers between projected cap and actual LMP that arise due to high FMM LMPs during the September heat event.

Figure 14: Difference for Methodology 29, summer 2022

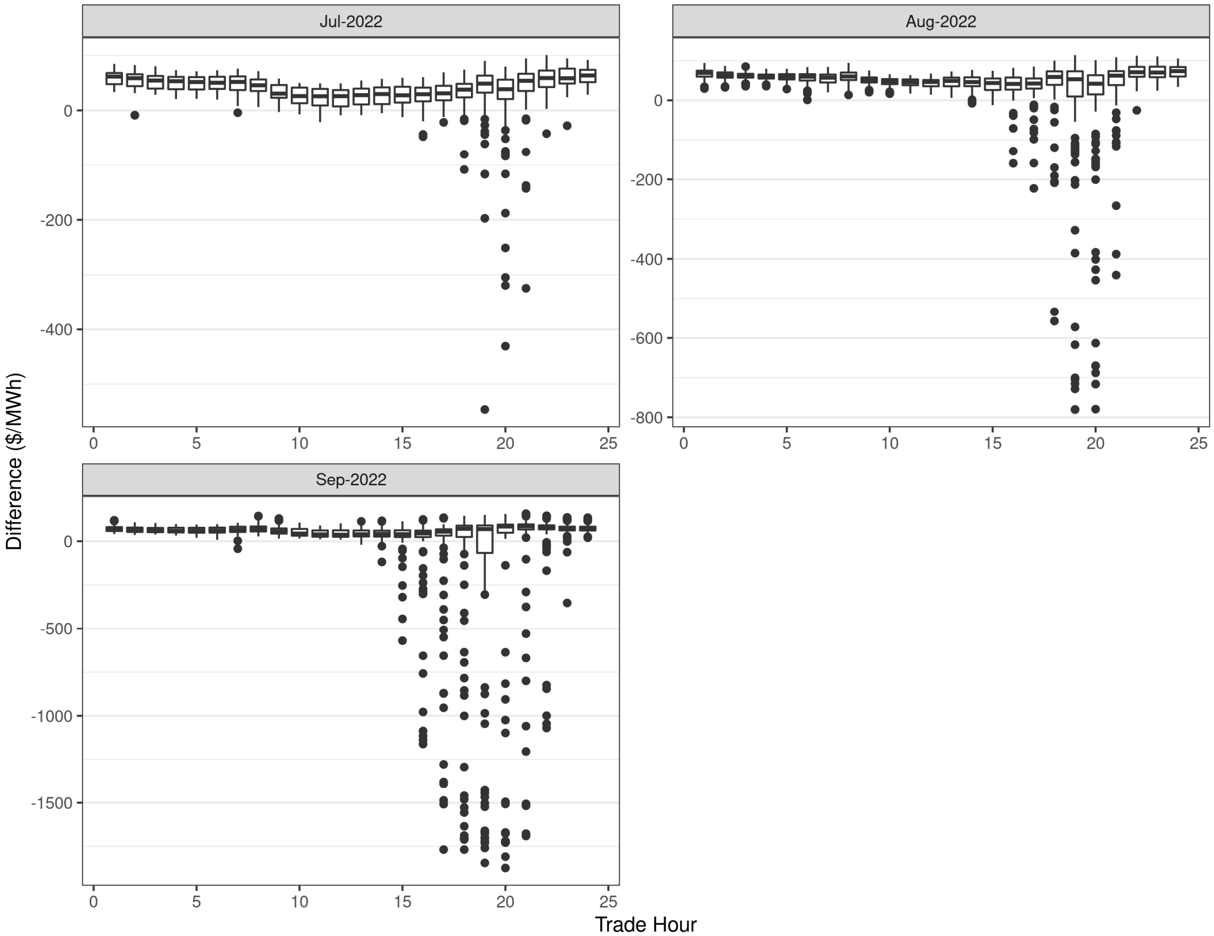


Table 6: Results for Methodology 29, summer 2022

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
July 2022	96.61%	43.64	40.57	0.65
August 2022	96.56%	60.84	46.58	0.67
September 2022	94.43%	106.27	13.65	0.76

Overall, methodologies 10 and 11[20] continued to perform favorably compared to the other tested methodologies during the summer months of 2022, as they did during the previous months of the year. Figure 15 below shows a comparison of the numerical metrics between the four tested methodologies for July through September 2022. The metrics, especially the closeness and difference metrics, saw more movement during months like September 2022 which had higher prices compared to previous months due to the heat event.

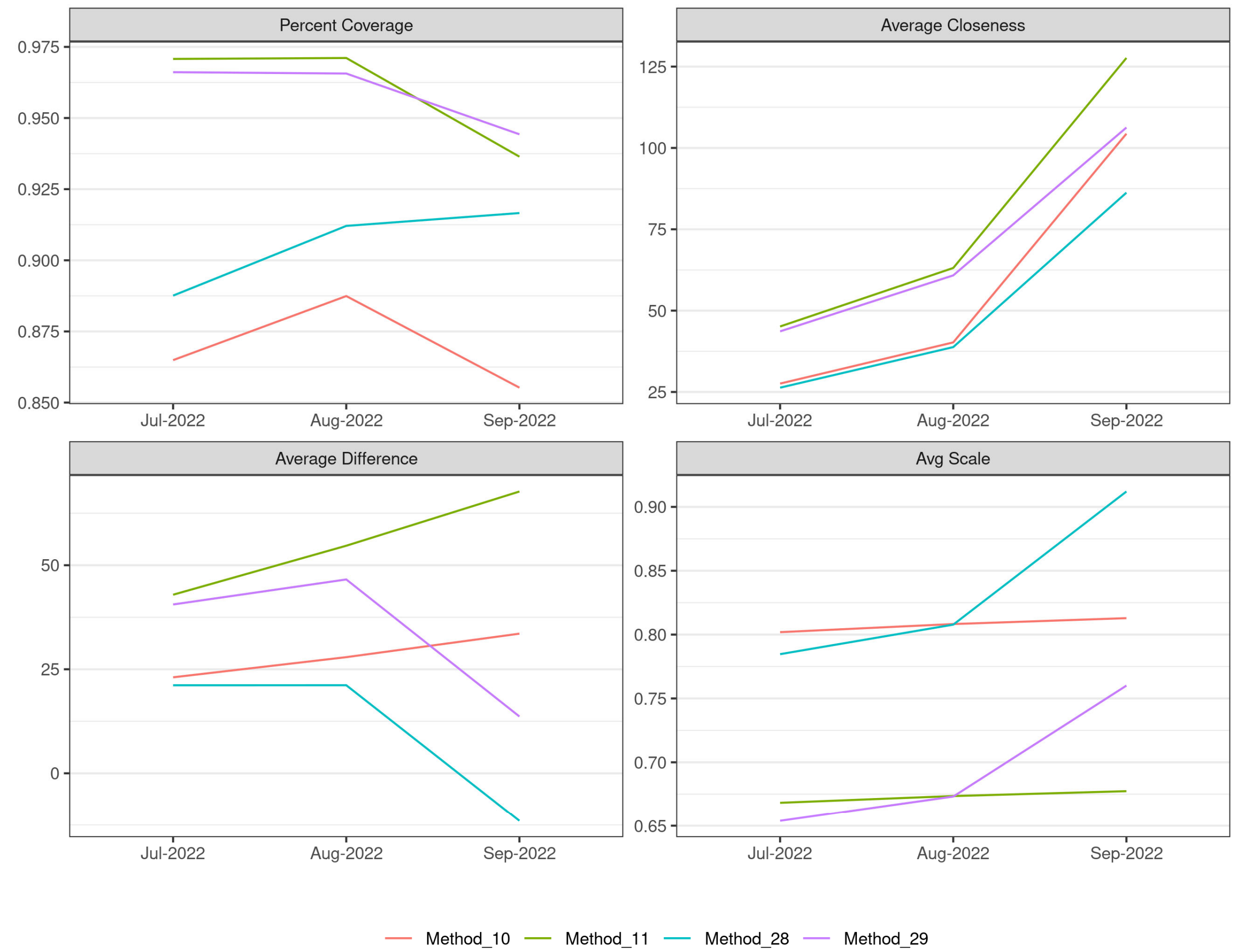
Methodology 11, whose metrics are shown in green below, outperformed the other three methodologies in context of the percent coverage metric; this indicates that methodology 11 did the best job at covering, i.e. not underestimating, the actual FMM prices compared to the other methodologies. However, the high coverage metric for methodology 11 is complemented by the lowest average scale metric; while it was sufficient at covering the actual FMM price, it often overestimated the projected price cap compared to the actual FMM price. While the companion methodology 10 shows lower percent coverage metrics during the summer months, it is complemented by a relatively high average scale value, meaning it did not overestimate the projected price cap as frequently as methodology 11.

The two methodologies that included both net load and average gas prices, methodologies 28 and 29[21], showed similar tradeoffs. For example, methodology 29 had higher coverage with lower scale, while methodology 28 had lower coverage with higher scale. This mirrors the movement discussed above for methodologies 10 and 11. These trends indicate that while the addition of a scalar may help improve the coverage metric, it can drive the scale metric lower, indicating that the projected cap is an overestimation of the actual FMM price.

[20] Both methodologies have common features of average gas price, 90^{th} quantile linear regression, and 60/60 lookback period; methodology 11 includes a 1.2 scalar on the projected price cap while methodology 10 does not include a scalar.

[21] Both methodologies have common features of average gas price and net load, 90^{th} quantile linear regression, 60/60 lookback period; methodology 29 includes a 1.2 scalar on the projected price cap while methodology 28 does not.

Figure 15: Comparison of metrics for incremental methodologies tested, summer 2022



4. Appendix

Methodologies 1 - 19: FMM LMPs vs Average Gas Price

Table 7. Methodology 1: Linear, 97.5, 30/30, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.35%	30.28	29.57	0.66
February 2022	96.06%	35.65	34.73	0.55
March 2022	97.17%	37.76	36.56	0.53
April 2022	95.76%	69.61	65.88	0.55
May 2022	96.17%	61.78	59.00	0.55
June 2022	96.35%	87.25	85.50	0.58

Figure 16. Hourly boxplot of difference, methodology 1: Linear, 97.5, 30/30, 15 min

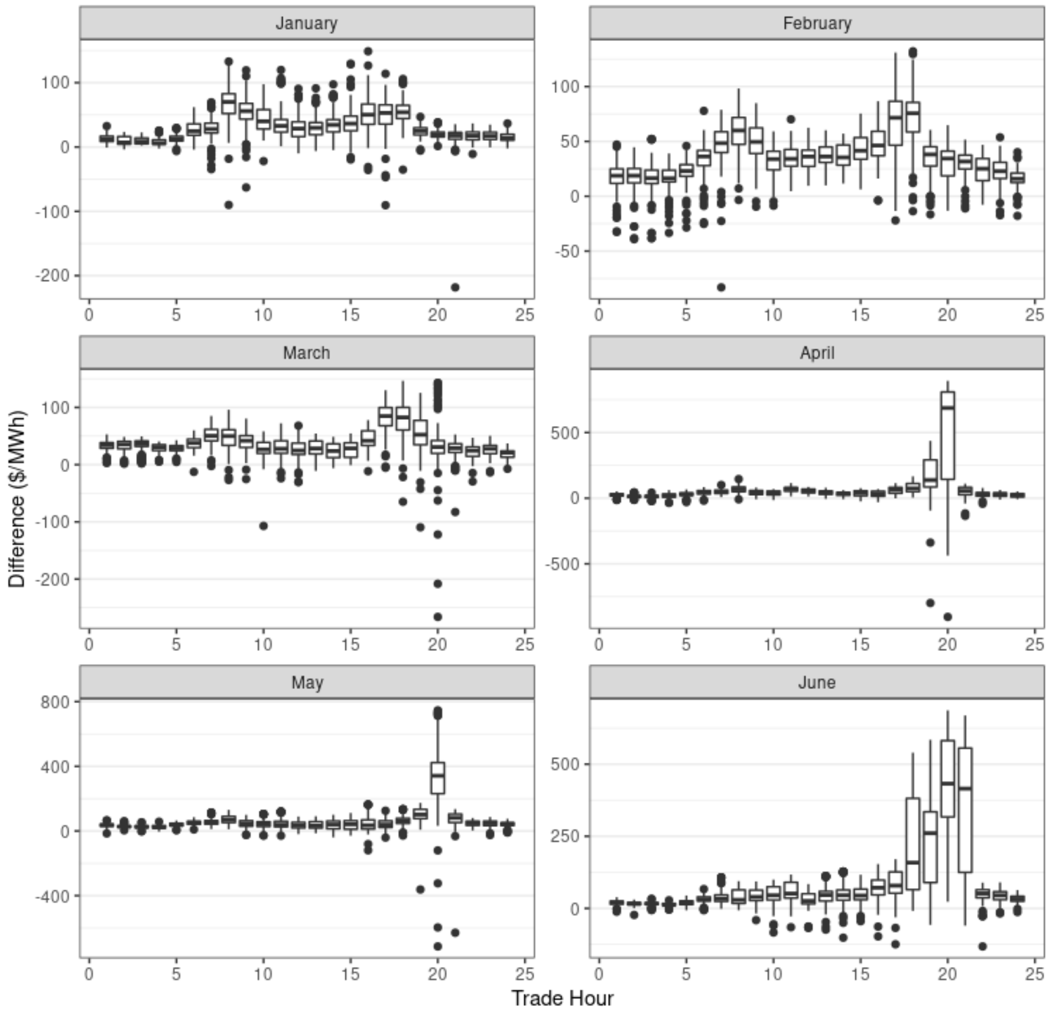


Figure 17. Hourly boxplot of scale, methodology 1: Linear, 97.5, 30/30, 15 min

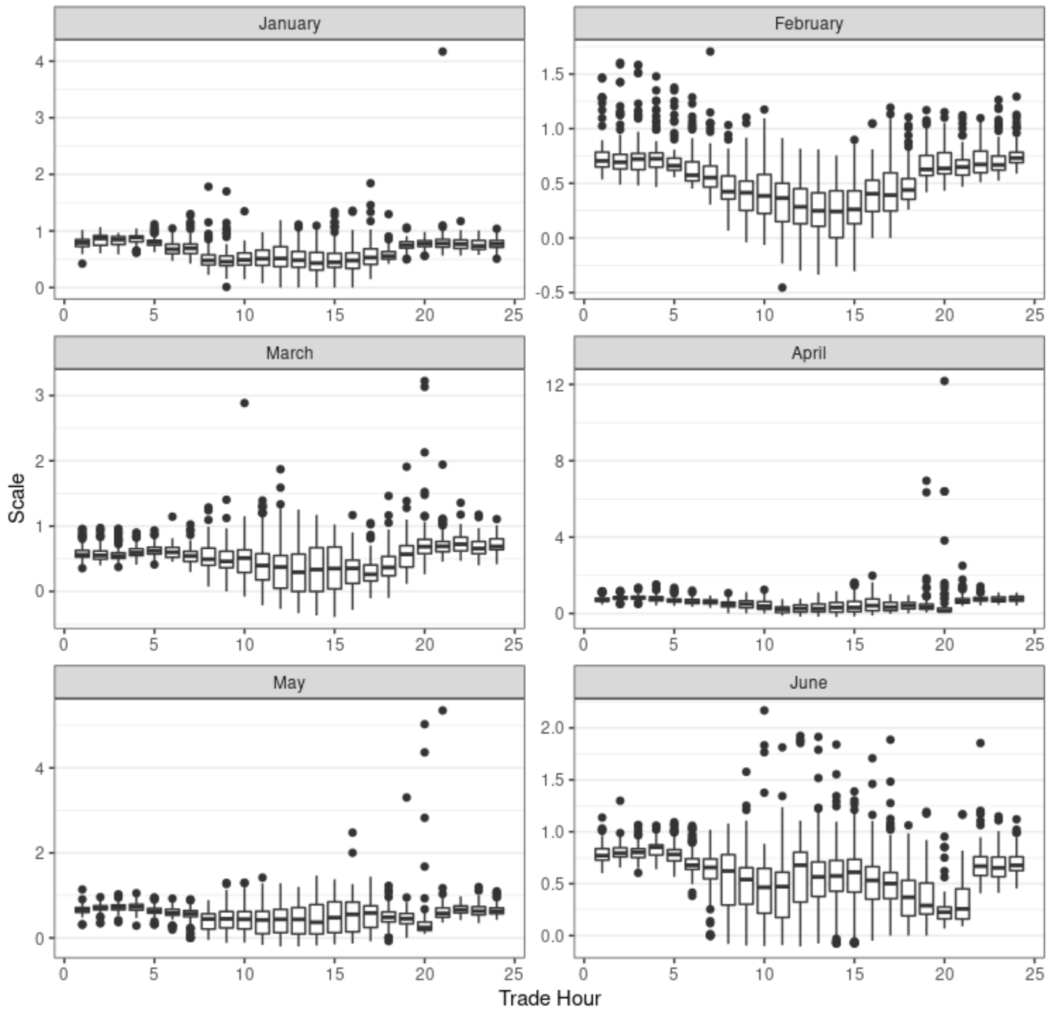


Table 8. Methodology 2: Linear, 97.5, 45/45, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.72%	33.28	32.60	0.62
February 2022	95.98%	36.89	35.85	0.54
March 2022	97.34%	38.97	37.72	0.52
April 2022	96.77%	71.97	68.36	0.52
May 2022	96.77%	72.31	70.19	0.52
June 2022	95.83%	69.93	67.29	0.59

Figure 18. Hourly boxplot of difference, methodology 2: Linear, 97.5, 45/45, 15 min

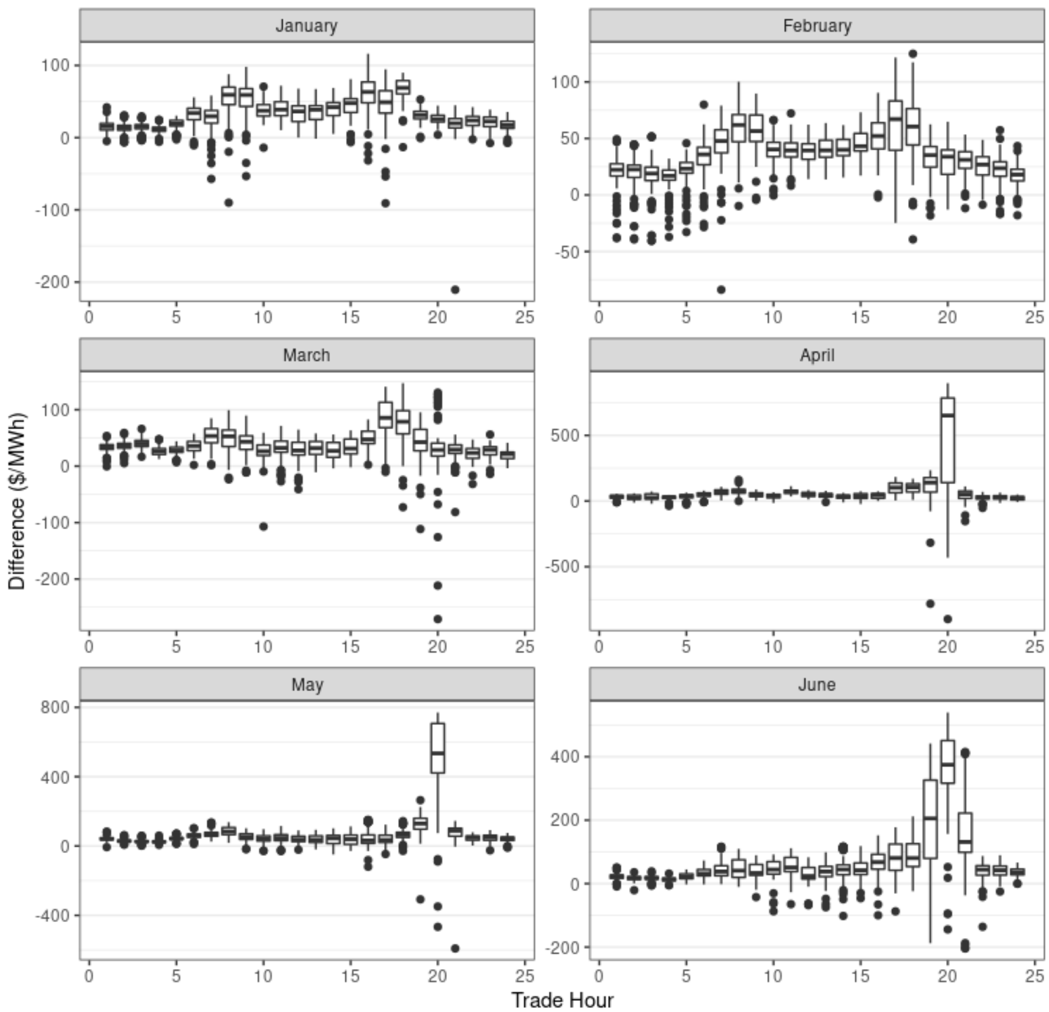


Figure 19. Hourly boxplot of scale, methodology 2: Linear, 97.5, 45/45, 15 min

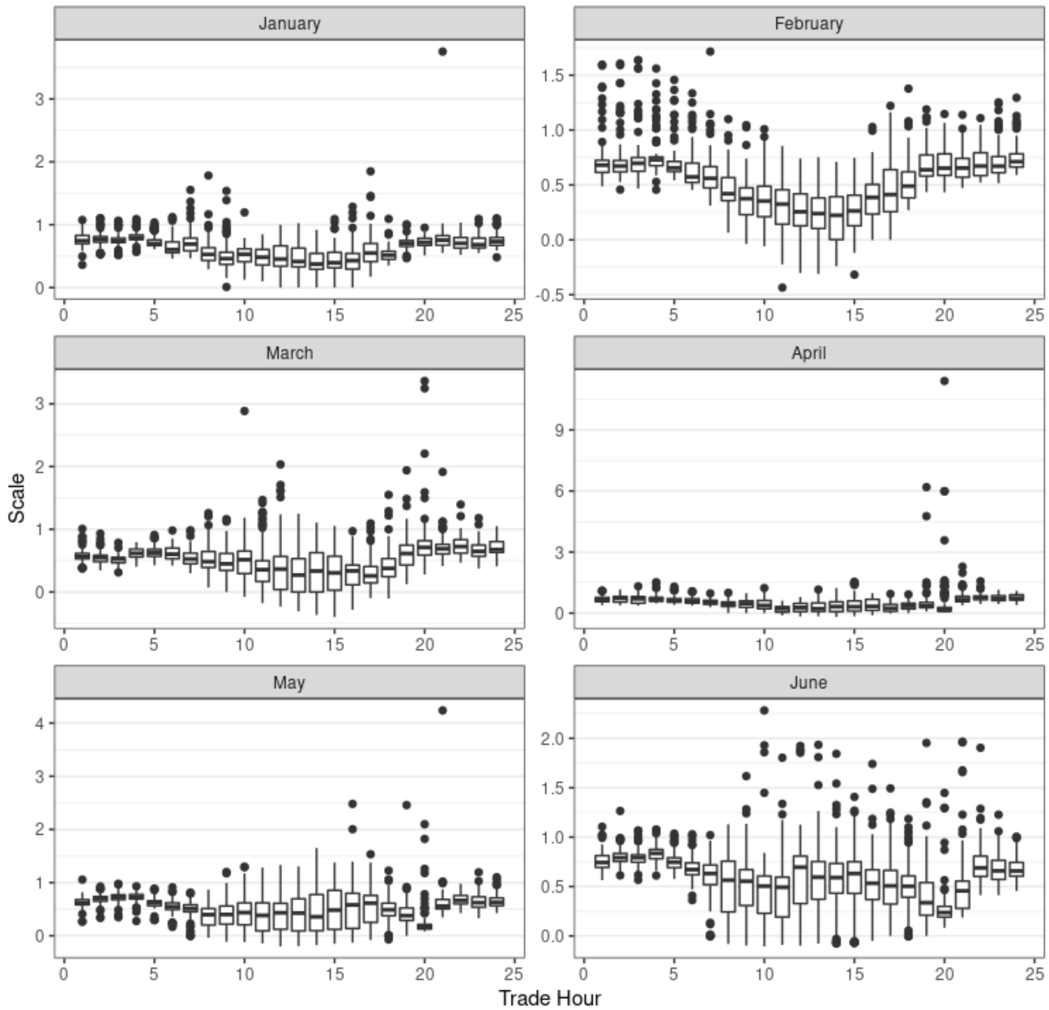


Table 9. Methodology 3: Linear, 97.5, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	99.19%	35.75	35.21	0.60
February 2022	96.32%	37.32	36.20	0.54
March 2022	97.68%	37.88	36.73	0.53
April 2022	97.81%	73.95	70.80	0.49
May 2022	97.51%	81.35	79.87	0.51
June 2022	95.59%	64.04	60.92	0.59

Figure 20. Hourly boxplot of difference, methodology 3: Linear, 97.5, 60/60, 15 min

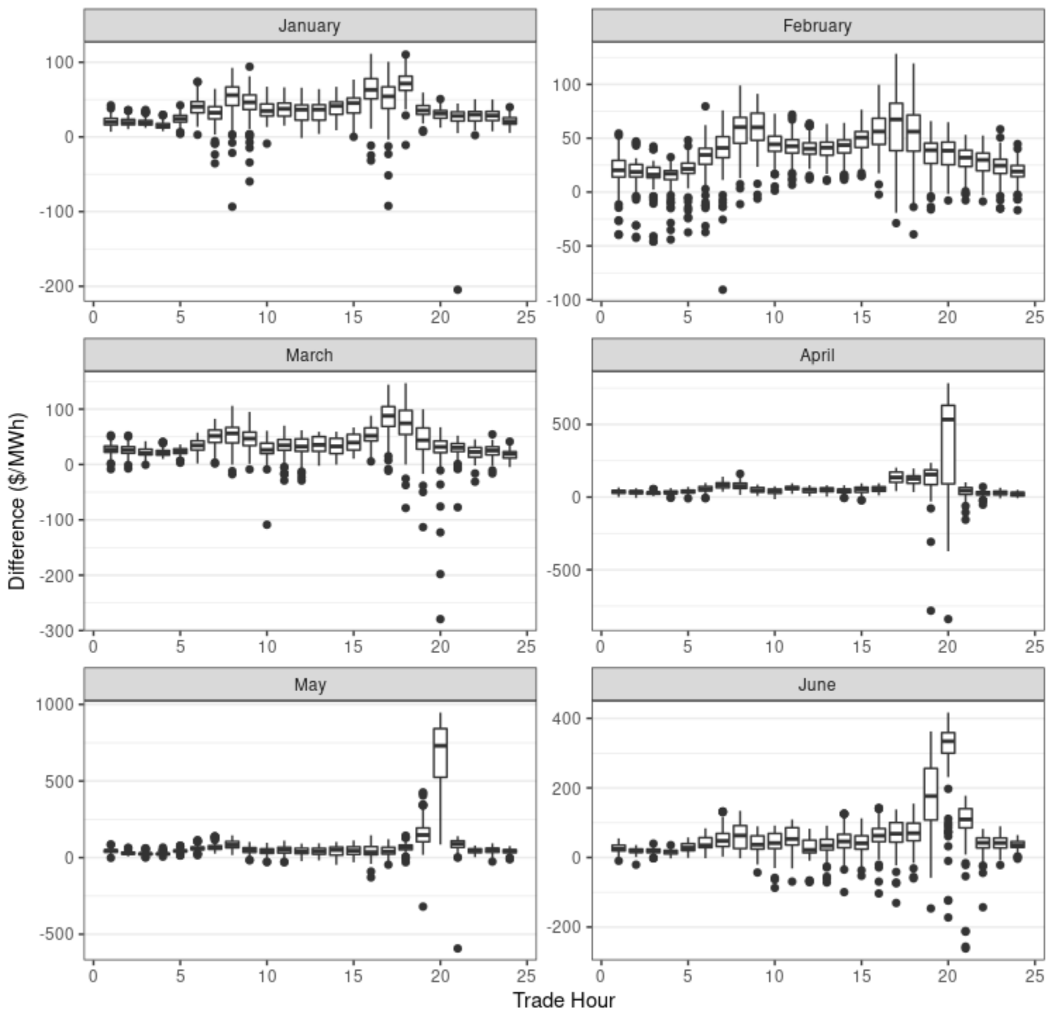


Figure 21. Hourly boxplot of scale, methodology 3: Linear, 97.5, 60/60, 15 min

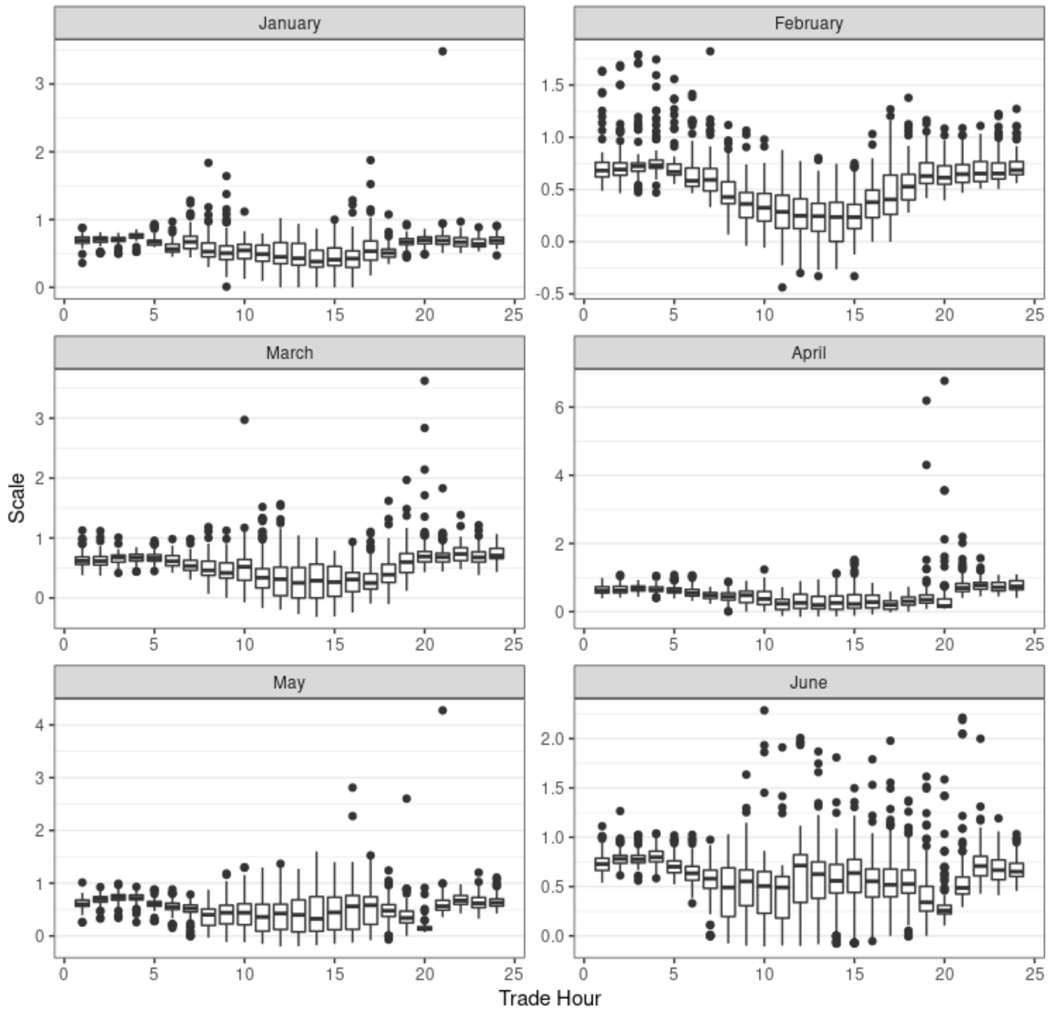


Table 10. Methodology 4: Linear, 97.5, 45/0, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	96.77%	33.03	32.29	0.65
February 2022	94.61%	30.85	29.54	0.60
March 2022	96.84%	37.68	36.29	0.54
April 2022	95.76%	78.09	74.87	0.53
May 2022	94.22%	53.60	50.36	0.57
June 2022	91.77%	61.22	56.28	0.63

Figure 22. Hourly boxplot of difference, methodology 4: Linear, 97.5, 45/0, 15 min

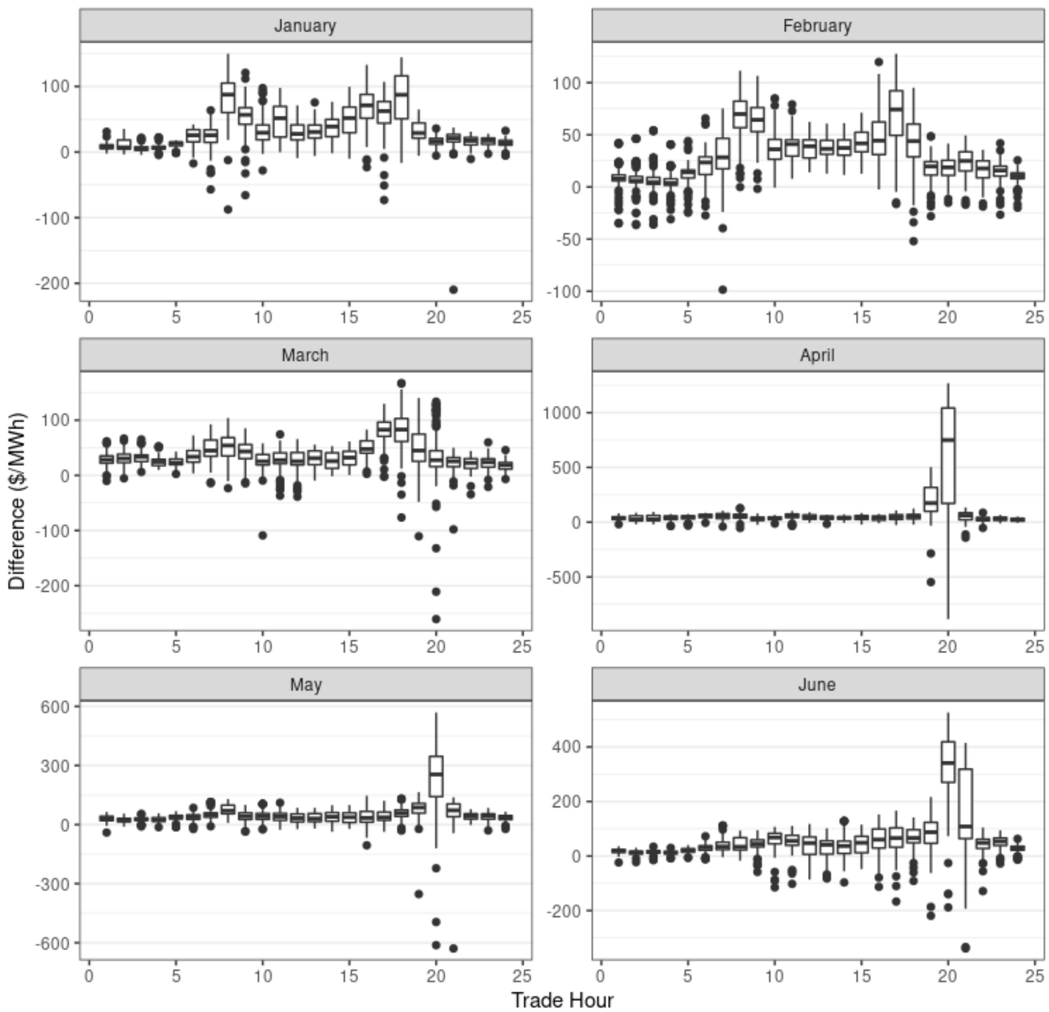


Figure 23. Hourly boxplot of scale, methodology 4: Linear, 97.5, 45/0, 15 min

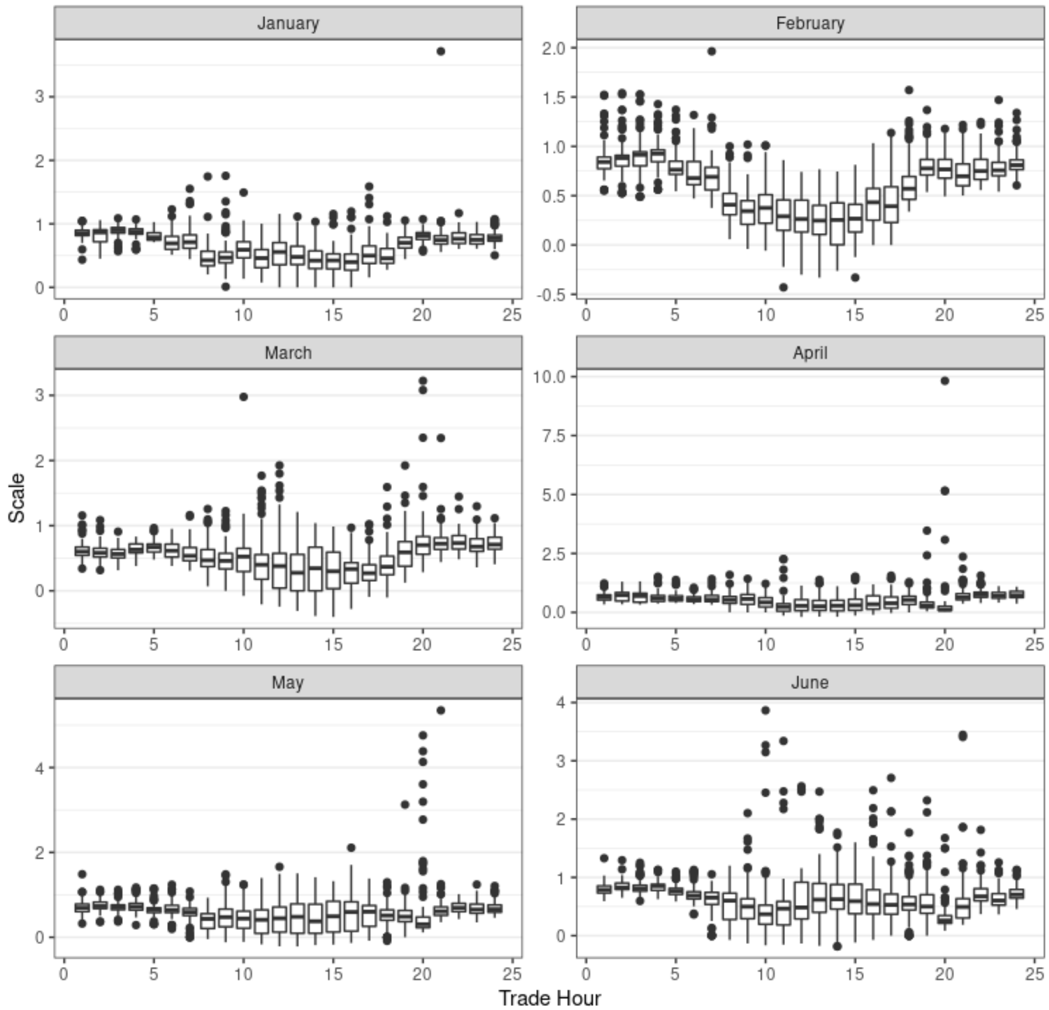


Table 11. Methodology 5: Linear, 97.5, 60/0, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.68%	33.44	32.79	0.65
February 2022	94.38%	30.77	29.22	0.61
March 2022	97.01%	37.25	35.93	0.54
April 2022	97.50%	78.67	75.94	0.50
May 2022	95.73%	64.54	61.75	0.55
June 2022	93.79%	52.51	47.76	0.63

Figure 24. Hourly boxplot of difference, methodology 5: Linear, 97.5, 60/0, 15 min

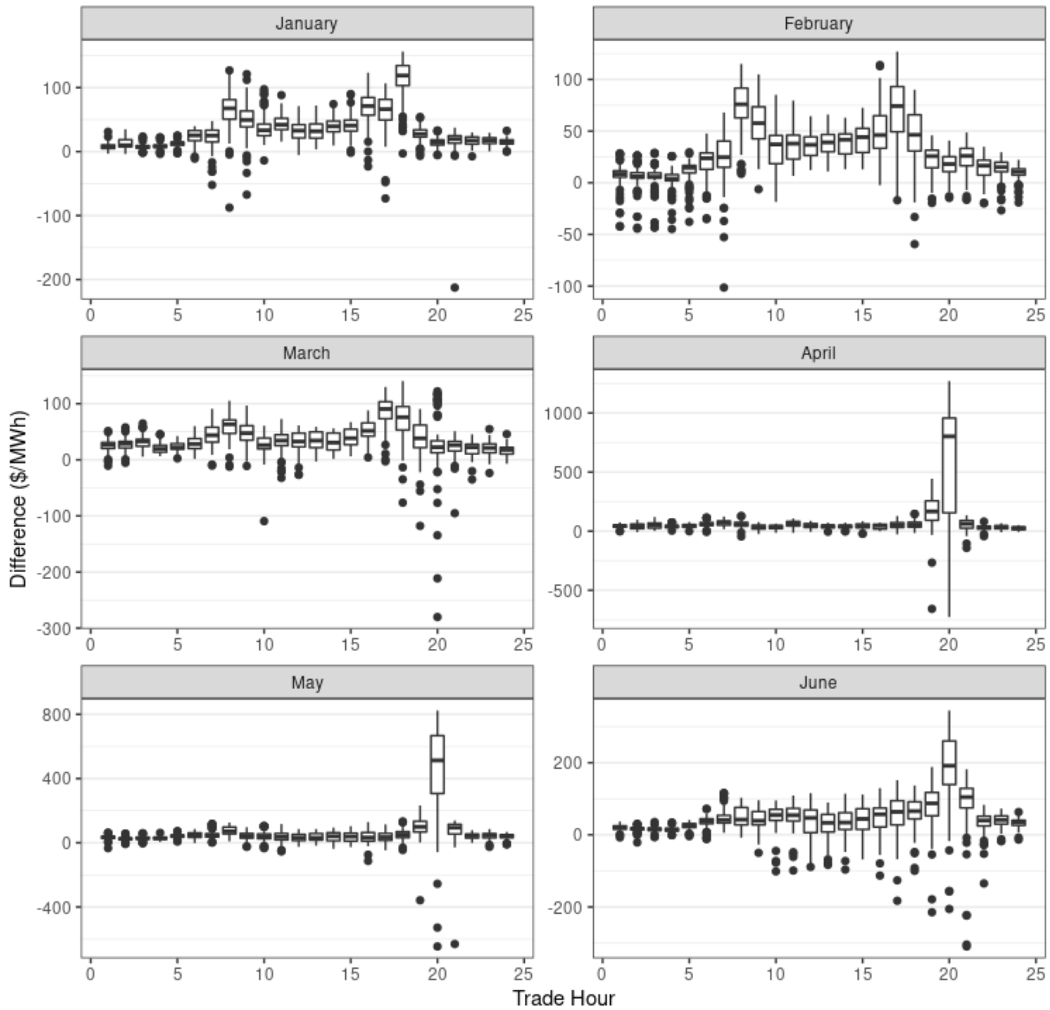


Figure 25. Hourly boxplot of scale, methodology 5: Linear, 97.5, 60/0, 15 min

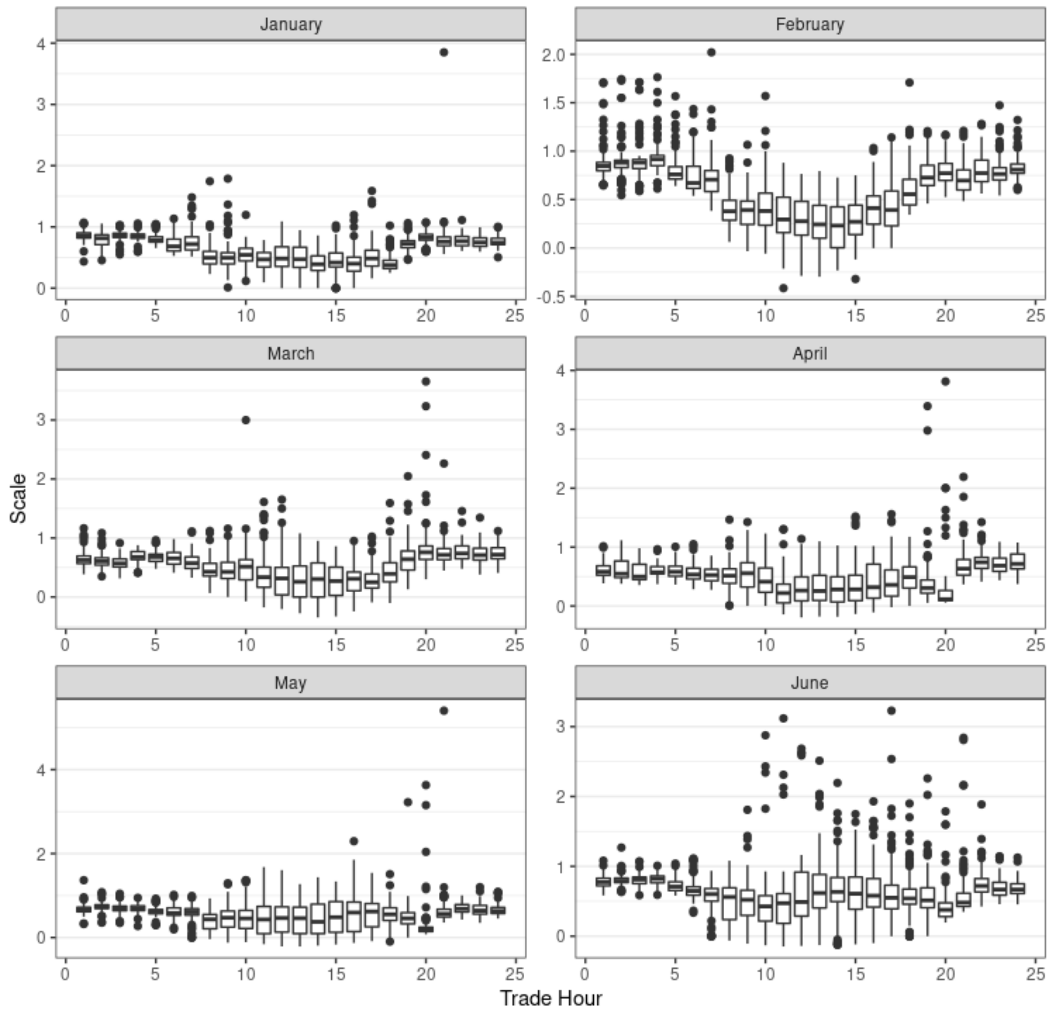


Table 12. Methodology 6: Linear, 97.5, 90/0, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.65%	33.13	32.40	0.65
February 2022	94.79%	34.90	33.51	0.59
March 2022	96.77%	36.44	35.11	0.55
April 2022	98.16%	73.00	69.95	0.49
May 2022	95.73%	76.80	74.39	0.52
June 2022	94.34%	57.86	53.58	0.63

Figure 26. Hourly boxplot of difference, methodology 6: Linear, 97.5, 90/0, 15 min

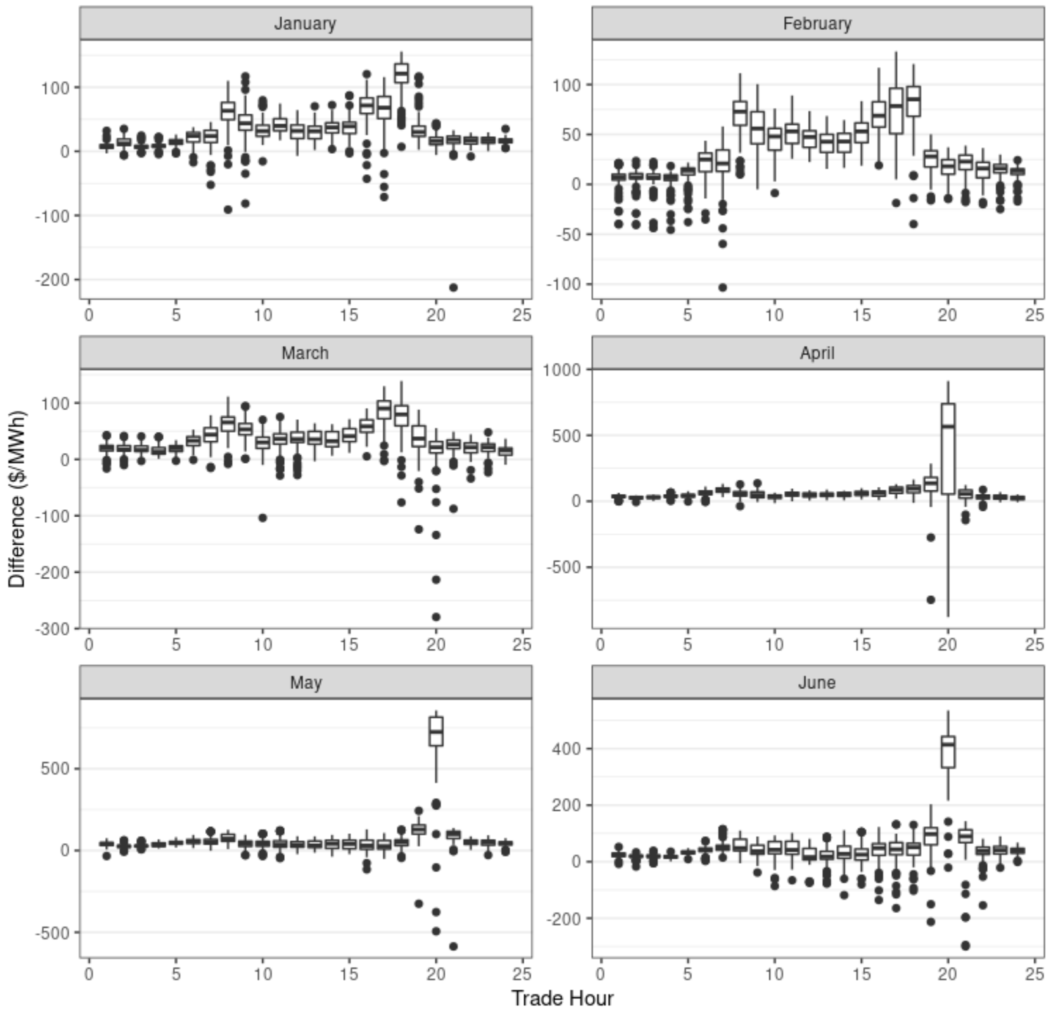


Figure 27. Hourly boxplot of scale, methodology 6: Linear, 97.5, 90/0, 15 min

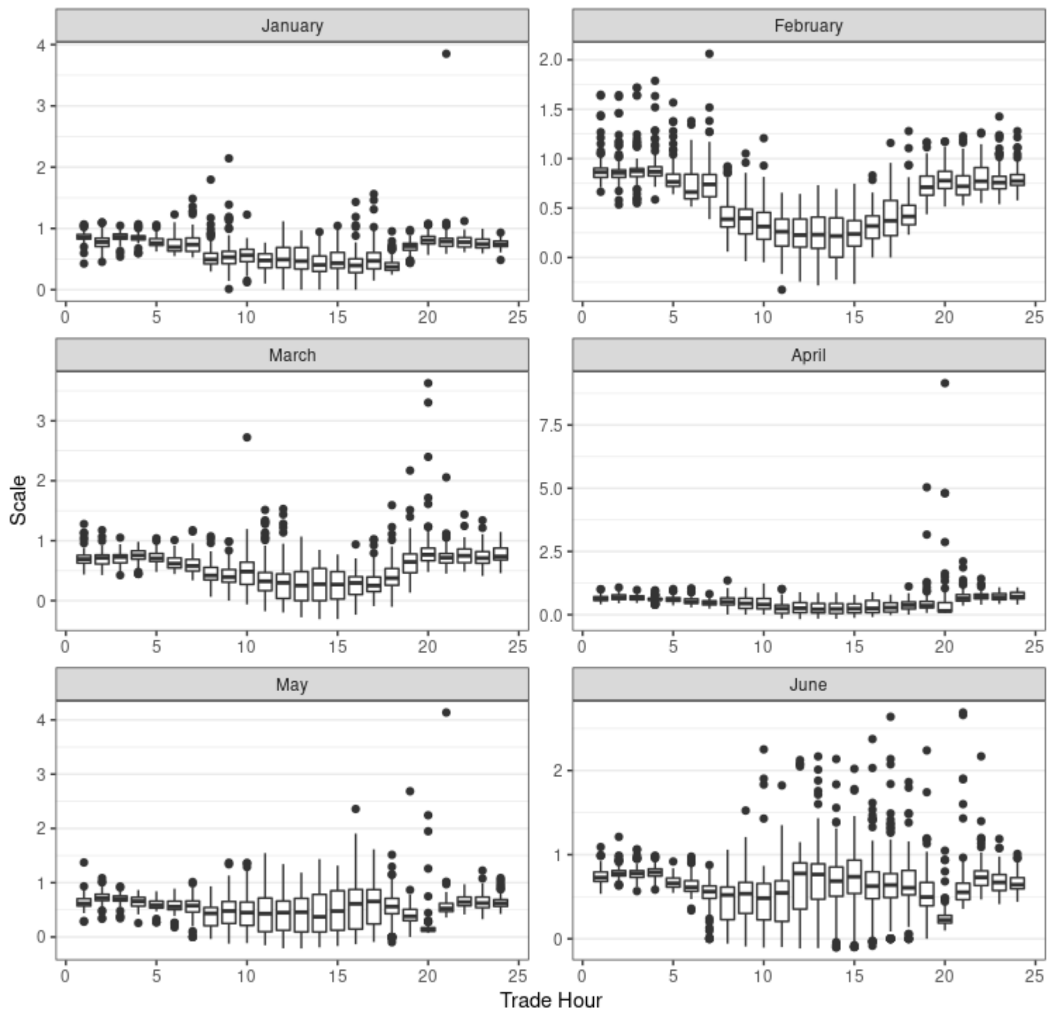


Table 13. Methodology 7: Linear, 90, 30/30, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	87.33%	16.40	14.08	0.79
February 2022	88.69%	20.94	18.08	0.68
March 2022	91.29%	22.69	20.01	0.66
April 2022	88.37%	31.09	24.98	0.67
May 2022	91.53%	35.64	31.20	0.65
June 2022	86.98%	30.67	23.48	0.75

Figure 28. Hourly boxplot of difference, methodology 7: Linear, 90, 30/30, 15 min

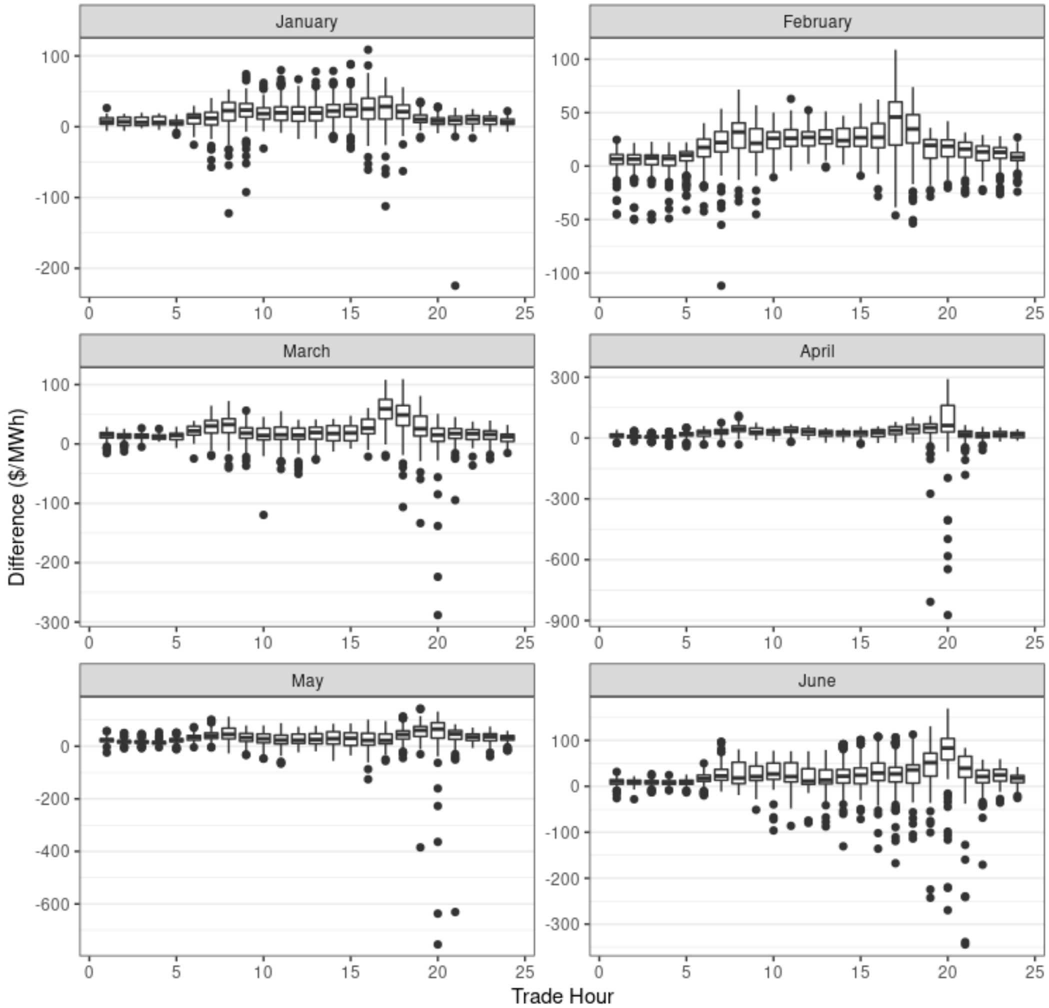


Figure 29. Hourly boxplot of scale, methodology 7: Linear, 90, 30/30, 15 min

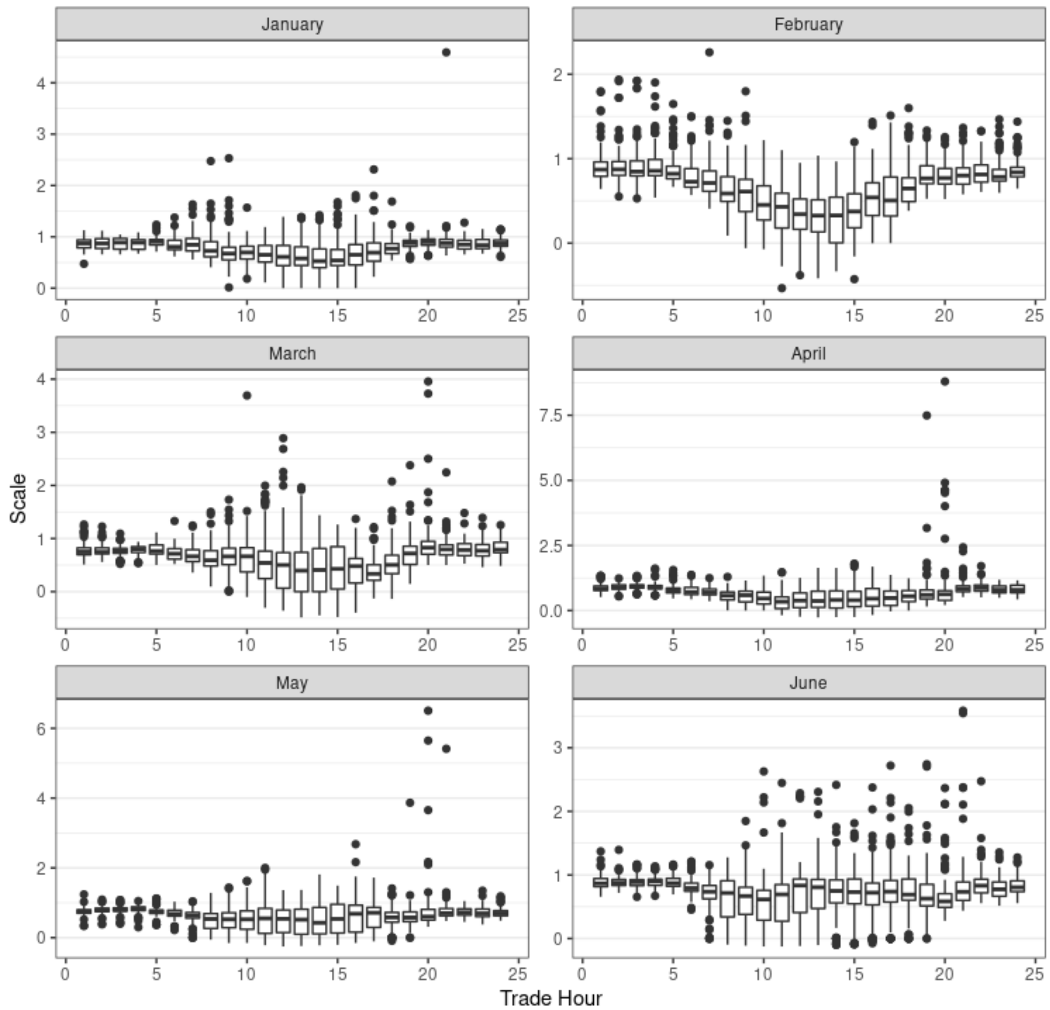


Table 14. Methodology 8: Linear, 90, 30/30, 1.1 scalar, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	95.16%	22.01	20.68	0.72
February 2022	93.45%	26.04	24.31	0.62
March 2022	94.38%	28.14	26.25	0.60
April 2022	93.79%	37.94	33.11	0.61
May 2022	95.26%	43.97	40.55	0.59
June 2022	92.57%	38.27	32.96	0.69

Figure 30. Hourly boxplot of difference, methodology 8: Linear, 90, 30/30, 1.1 scalar, 15 min

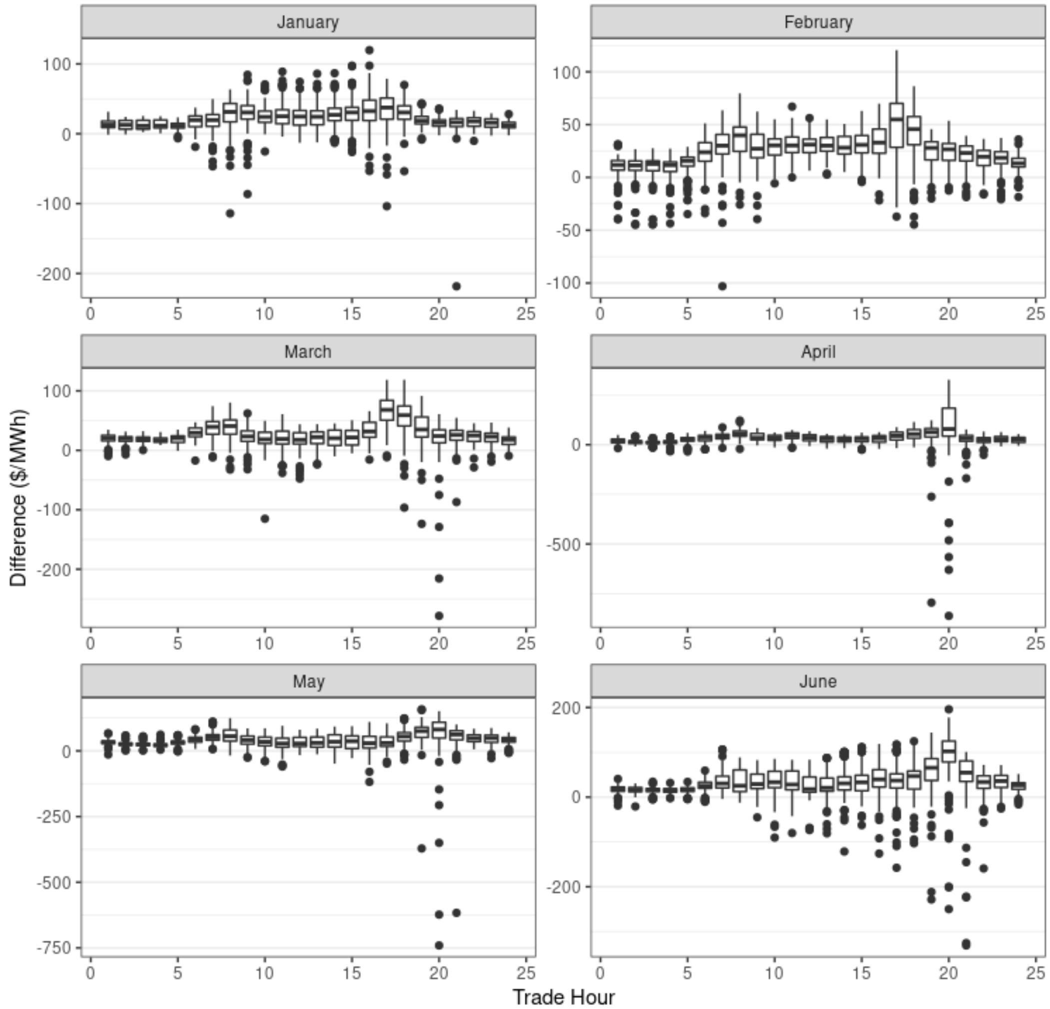


Figure 31. Hourly boxplot of scale, methodology 8: Linear, 90, 30/30, 1.1 scalar, 15 min

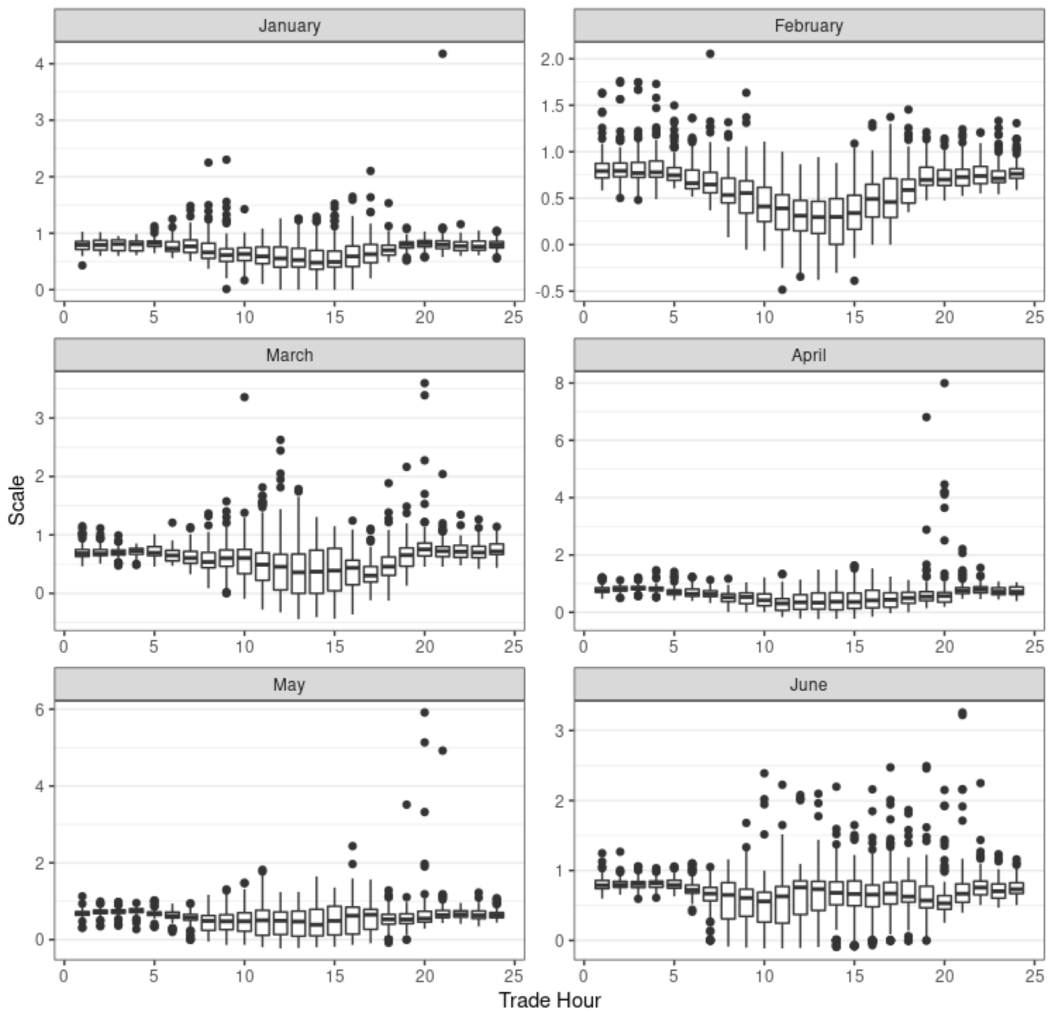


Table 15. Methodology 9: Linear, 90, 30/30, 1.2 scalar, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.55%	28.18	27.27	0.66
February 2022	96.13%	31.57	30.54	0.57
March 2022	96.30%	33.90	32.48	0.55
April 2022	96.08%	45.35	41.25	0.56
May 2022	96.91%	52.71	49.91	0.54
June 2022	95.17%	46.58	42.45	0.63

Figure 32. Hourly boxplot of difference, methodology 9: Linear, 90, 30/30, 1.2 scalar, 15 min

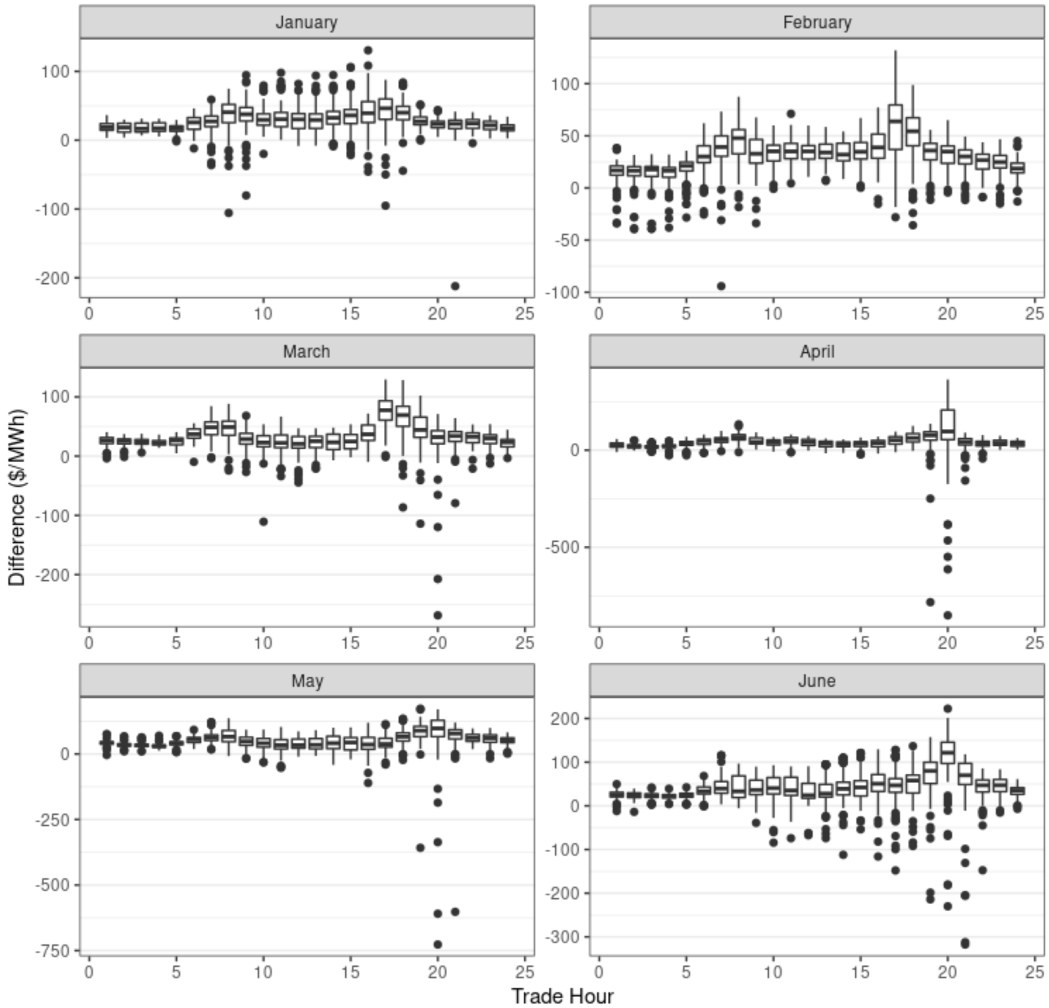


Figure 33. Hourly boxplot of scale, methodology 9: Linear, 90, 30/30, 1.2 scalar, 15 min

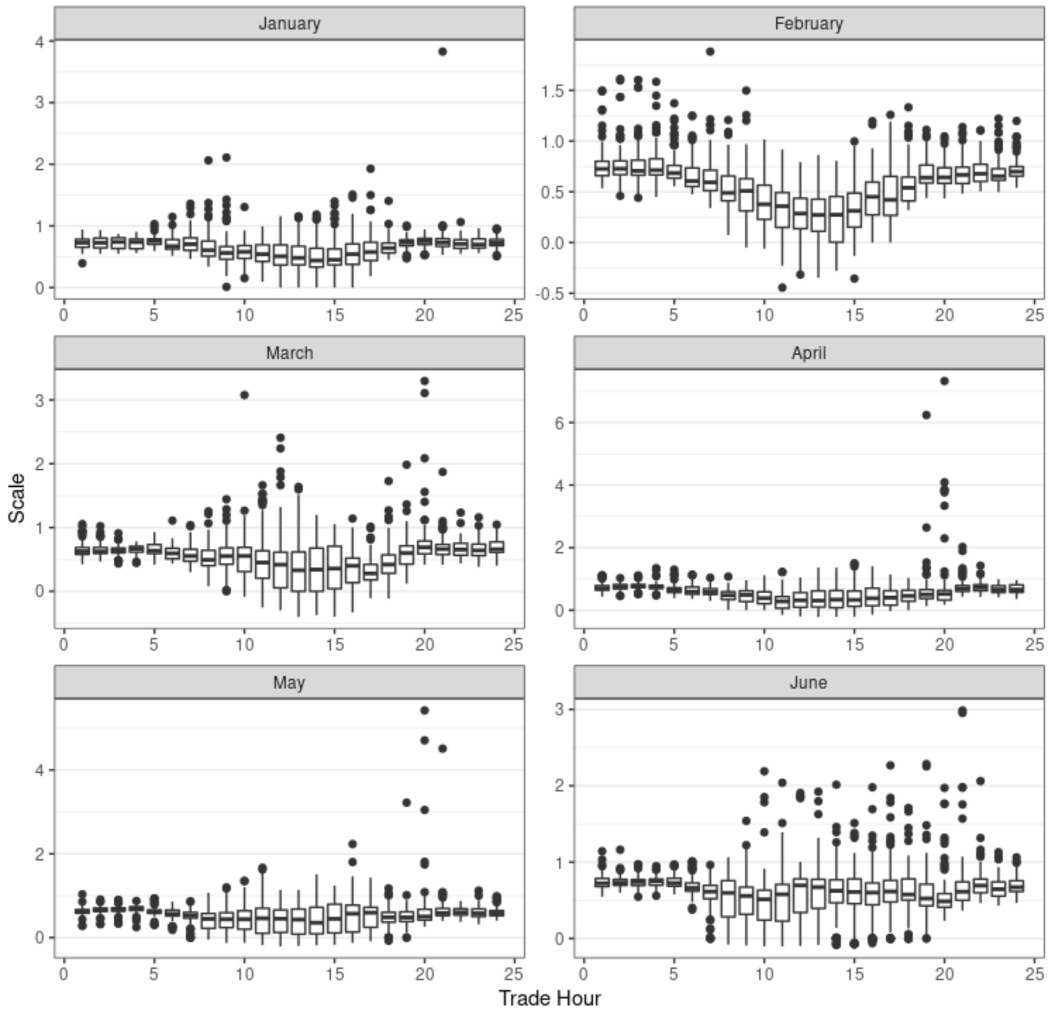


Table 16. Methodology 10: Linear, 90, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	91.16%	17.59	15.62	0.76
February 2022	89.32%	21.62	18.65	0.68
March 2022	90.11%	22.72	20.01	0.66
April 2022	91.35%	34.52	29.00	0.64
May 2022	93.78%	39.44	35.54	0.62
June 2022	87.74%	31.64	24.31	0.74

July 2022	86.30%	27.29	22.83	0.80
August 2022	88.74%	40.24	27.91	0.81
September 2022	85.52%	104.37	33.56	0.81

Figure 34. Hourly boxplot of difference, methodology 10: Linear, 90, 60/60, 15 min

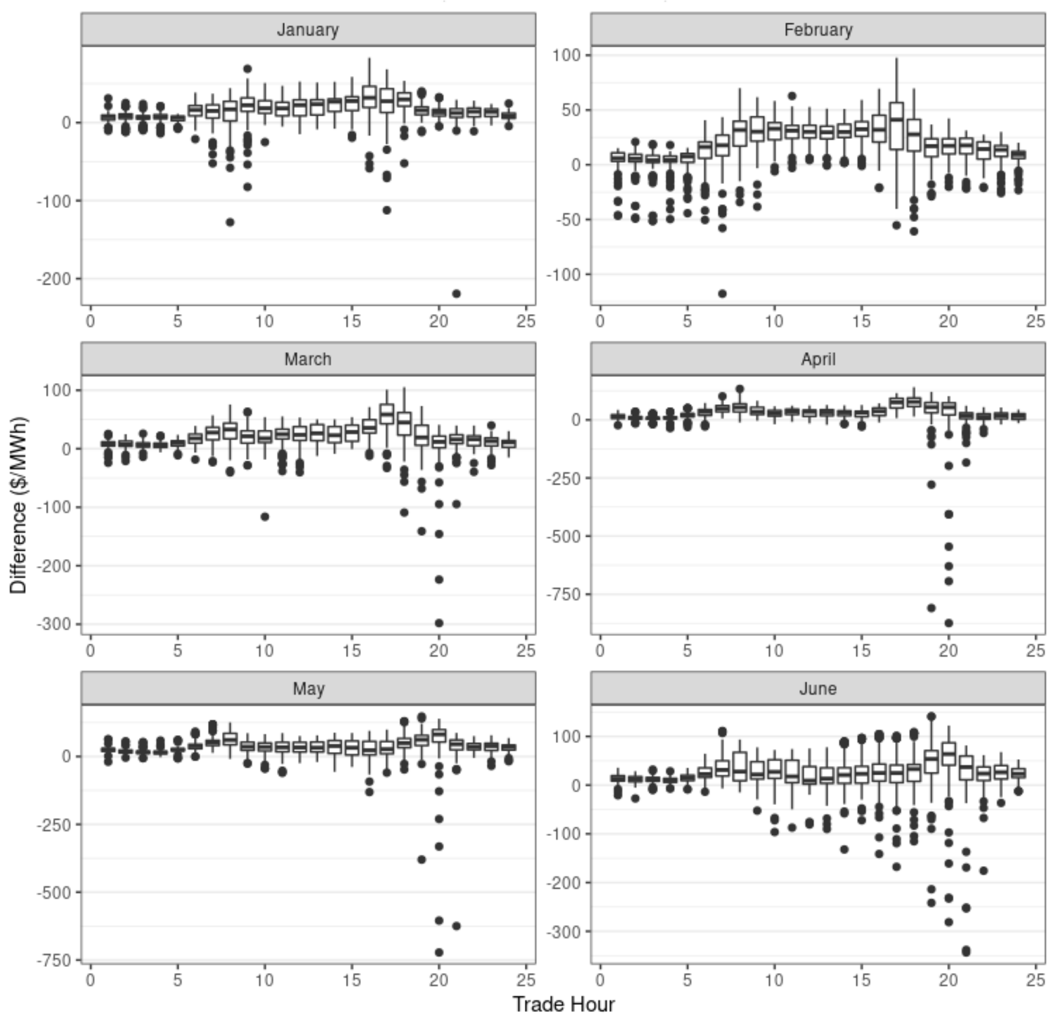


Figure 35. Hourly boxplot of difference, methodology 10: Linear, 90, 60/60, 15 min; summer 2022

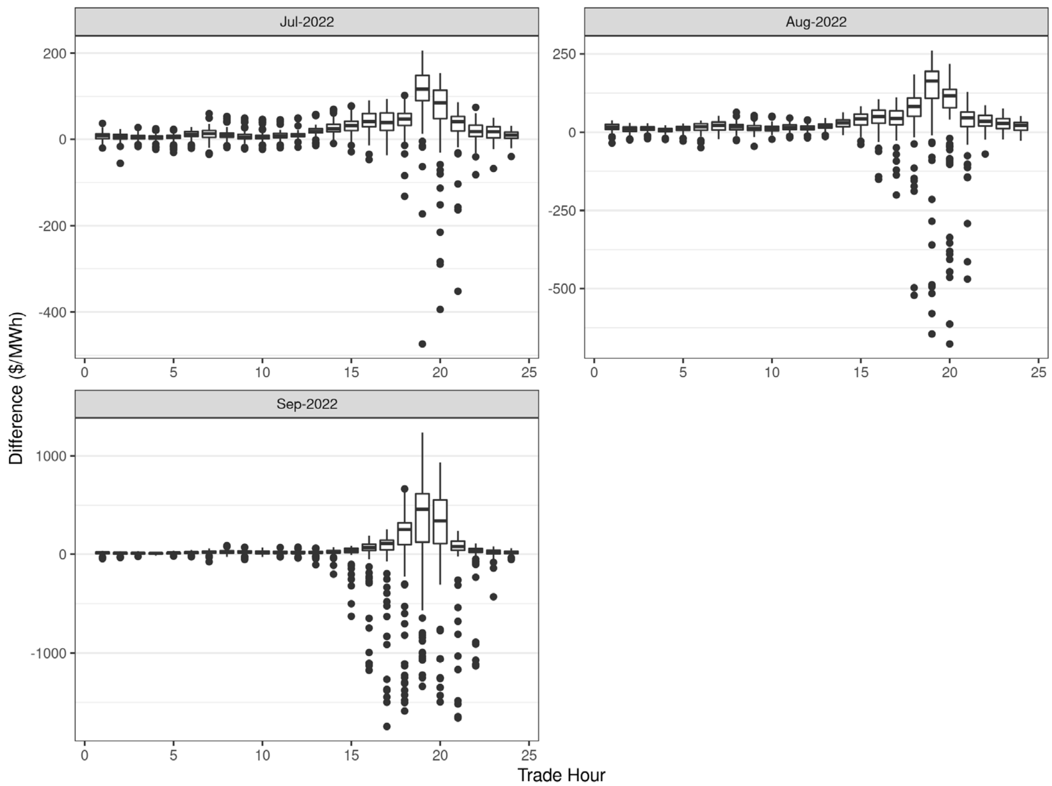


Figure 36. Hourly boxplot of scale, methodology 10: Linear, 90, 60/60, 15 min

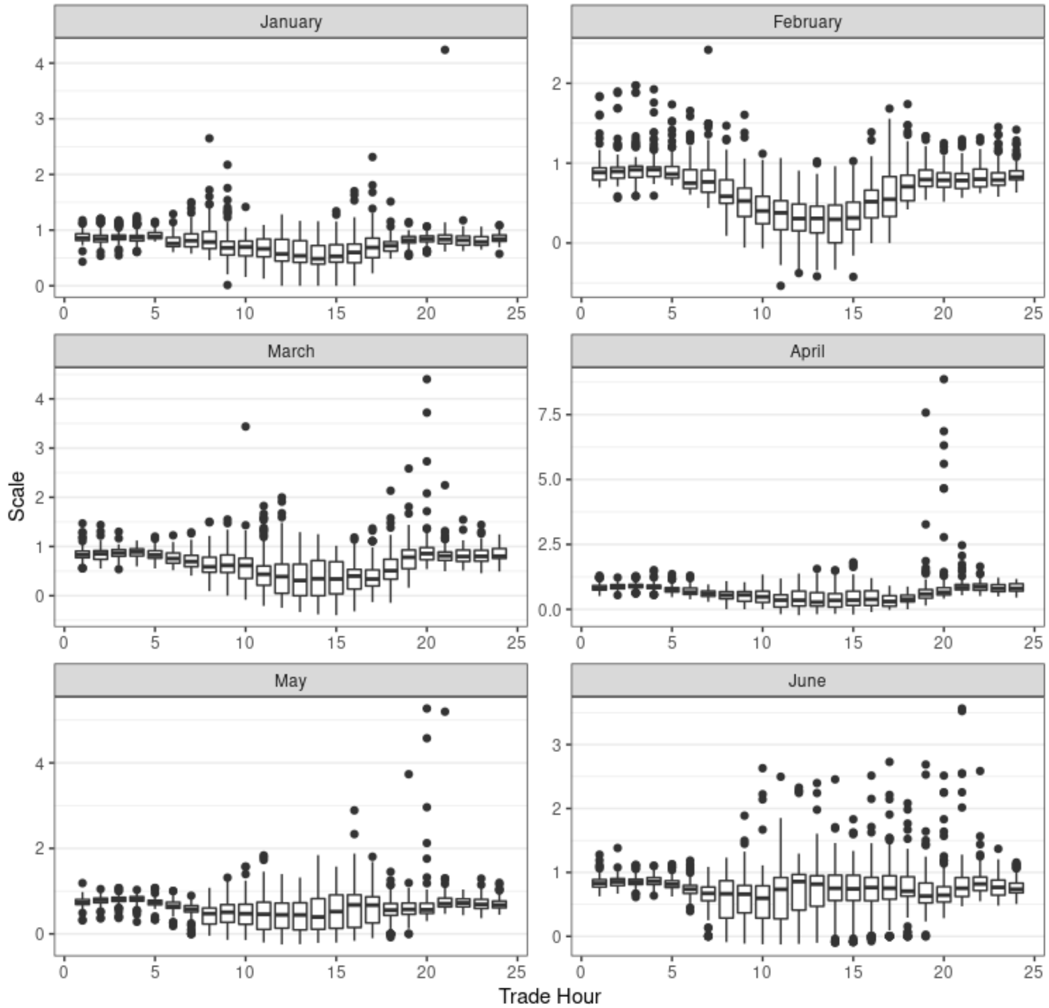


Figure 37. Hourly boxplot of scale, methodology 10: Linear, 90, 60/60, 15 min; summer 2022

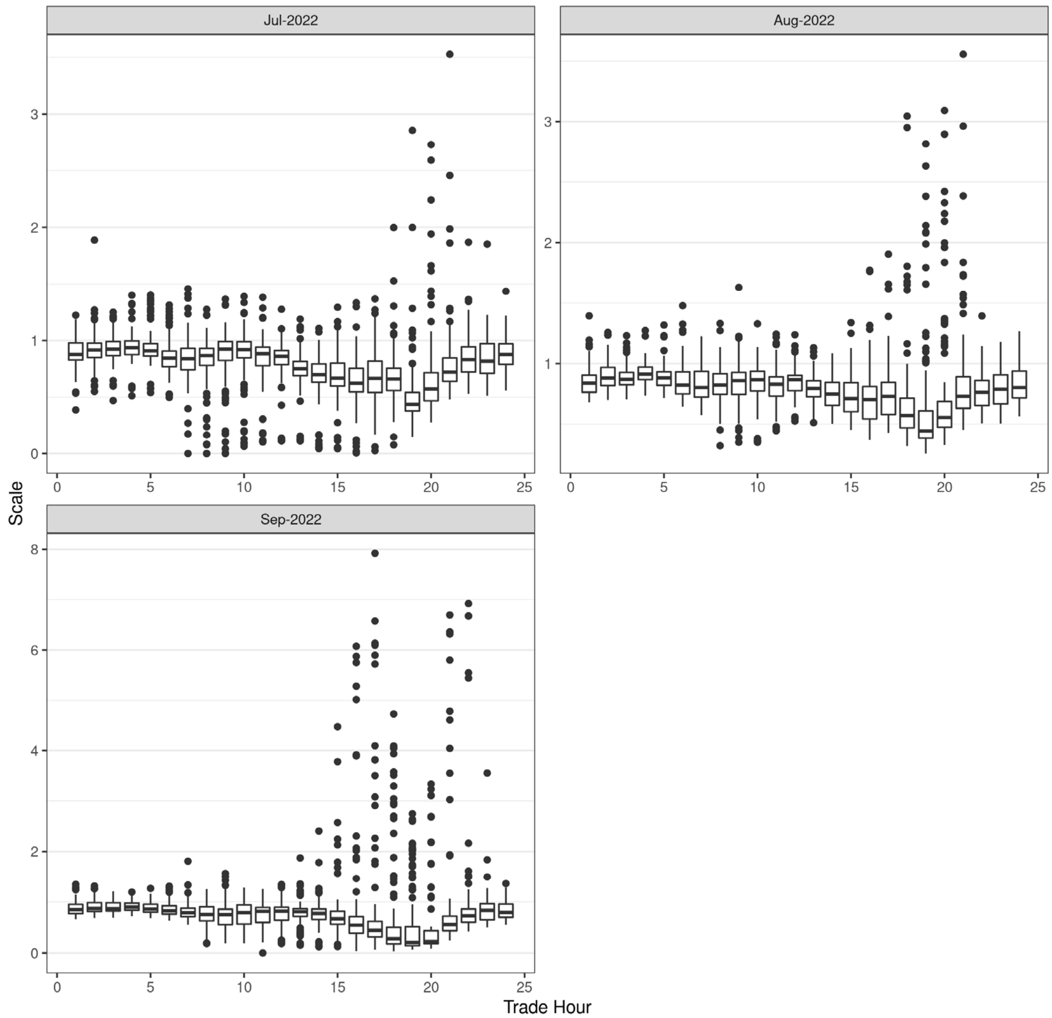


Table 17. Methodology 11: Linear, 90, 60/60, 1.2 scalar, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	98.42%	29.92	29.13	0.64
February 2022	96.13%	32.39	31.22	0.57
March 2022	97.21%	33.80	32.48	0.55
April 2022	97.57%	50.01	46.07	0.53
May 2022	97.78%	57.73	55.12	0.51
June 2022	95.21%	47.74	43.45	0.62

July 2022	97.08%	45.13	42.92	0.67
August 2022	97.11%	63.12	54.69	0.67
September 2022	93.64%	127.64	67.72	0.68

Figure 38. Hourly boxplot of difference, methodology 11: Linear, 90, 60/60, 1.2 scalar, 15 min

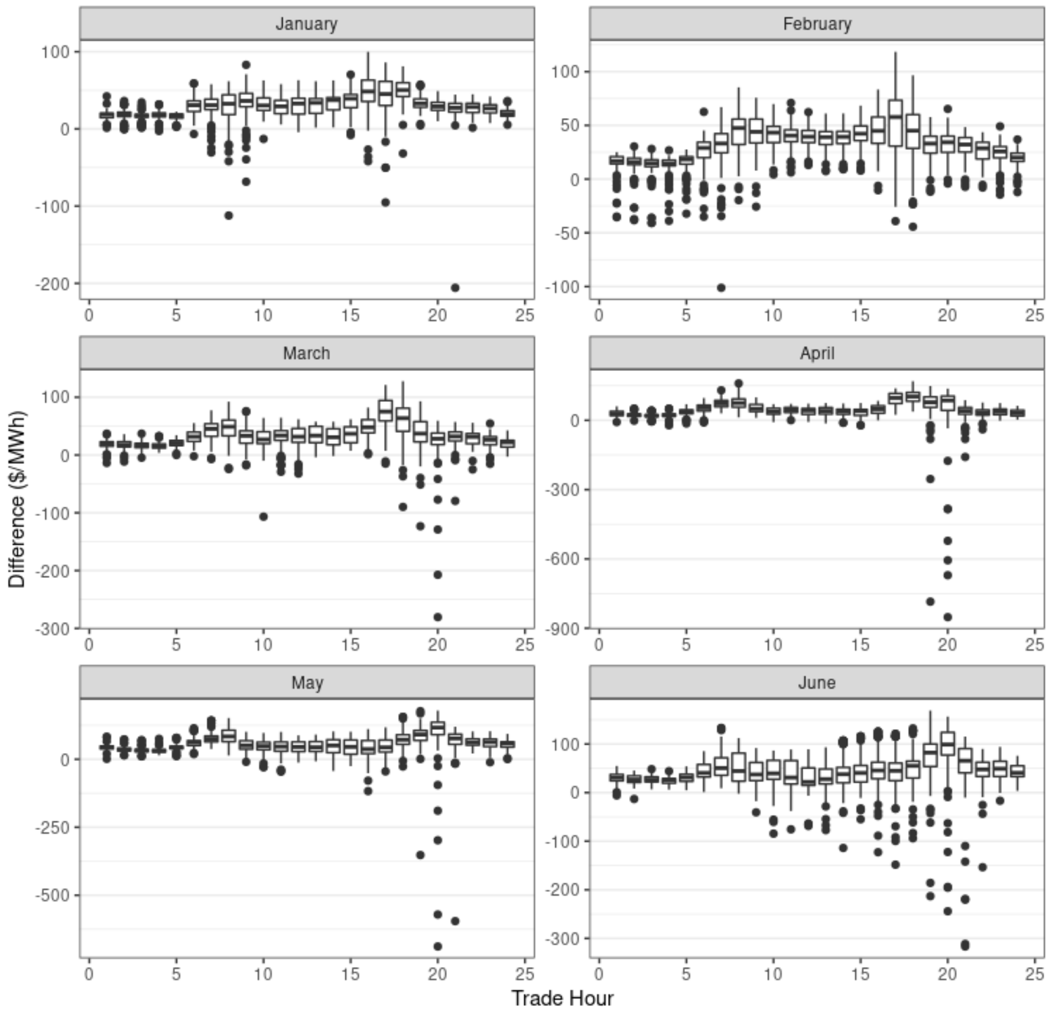


Figure 39. Hourly boxplot of difference, methodology 11: Linear, 90, 60/60, 1.2 scalar, 15 min; summer 2022

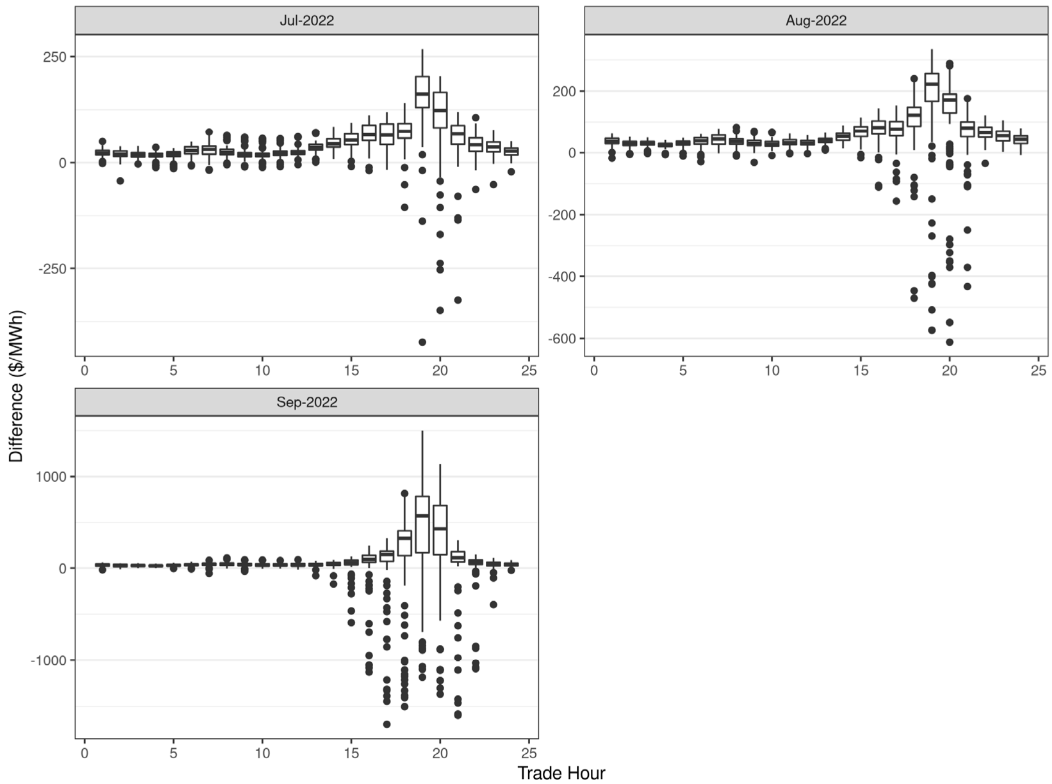


Figure 40. Hourly boxplot of scale, methodology 11: Linear, 90, 60/60, 1.2 scalar, 15 min

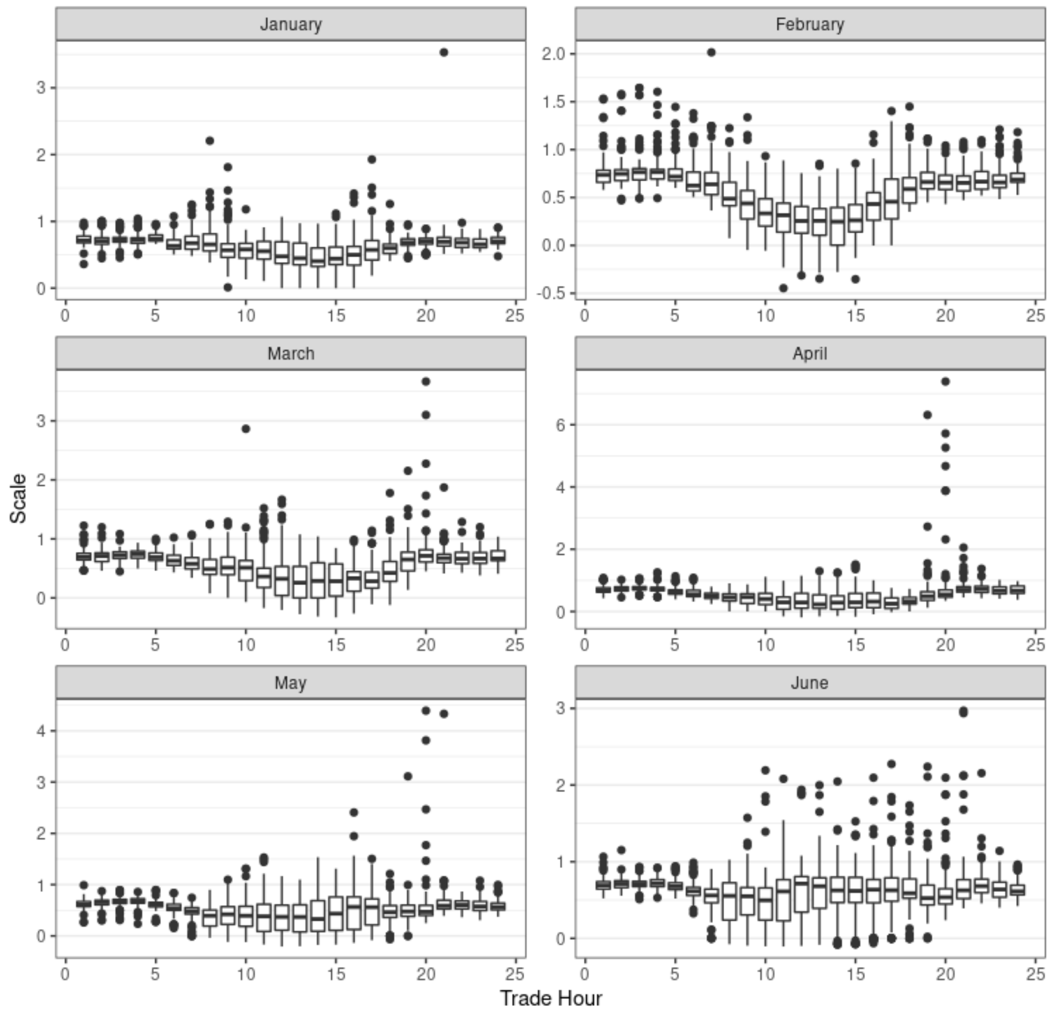


Figure 41. Hourly boxplot of scale, methodology 11: Linear, 90, 60/60, 1.2 scalar, 15 min; summer 2022

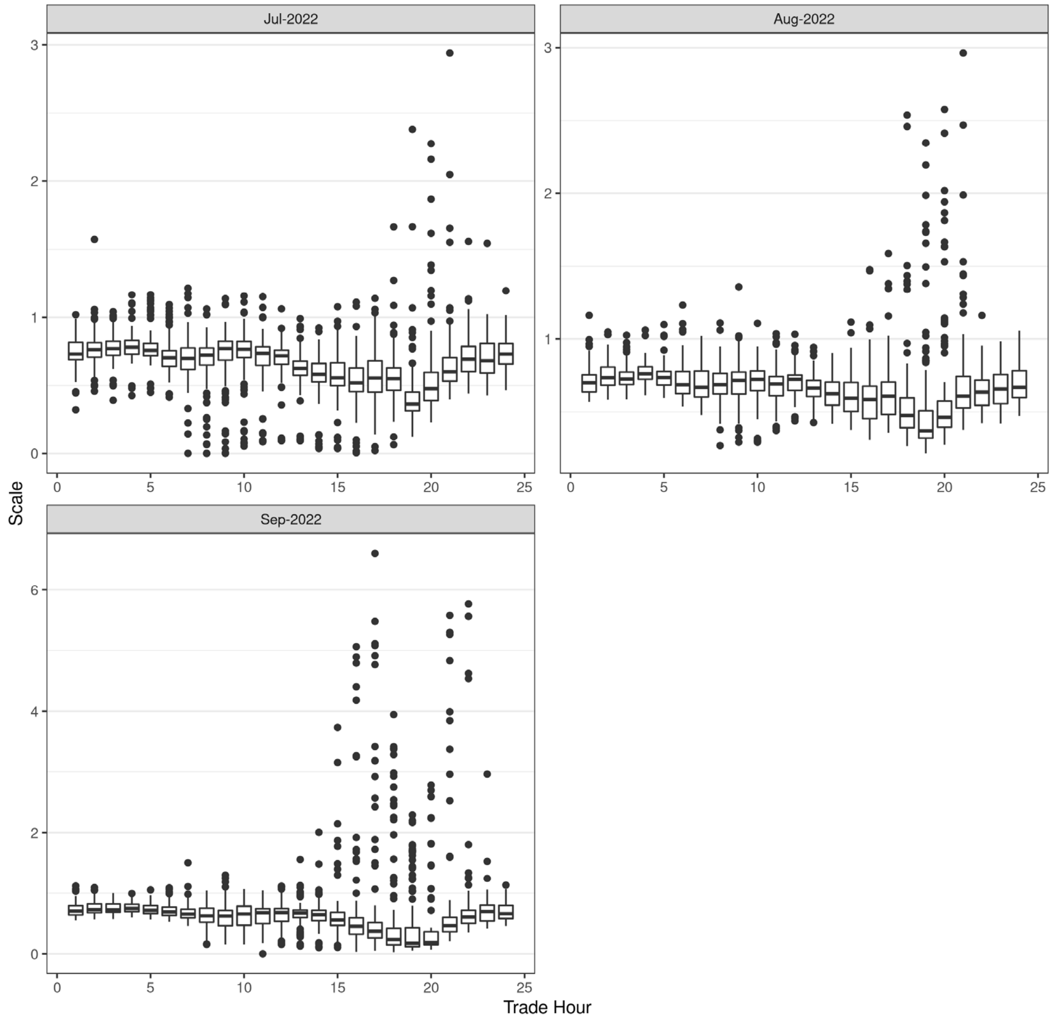


Table 18. Methodology 12: Linear, 97.5, 60/60, hourly

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	98.39%	32.44	31.64	0.62
February 2022	94.12%	32.00	30.02	0.58
March 2022	96.03%	32.32	30.81	0.56
April 2022	95.76%	71.71	68.13	0.52
May 2022	95.97%	85.83	84.06	0.53
June 2022	94.44%	61.02	57.34	0.62

Figure 42. Hourly boxplot of difference, methodology 12: Linear, 97.5, 60/60, hourly

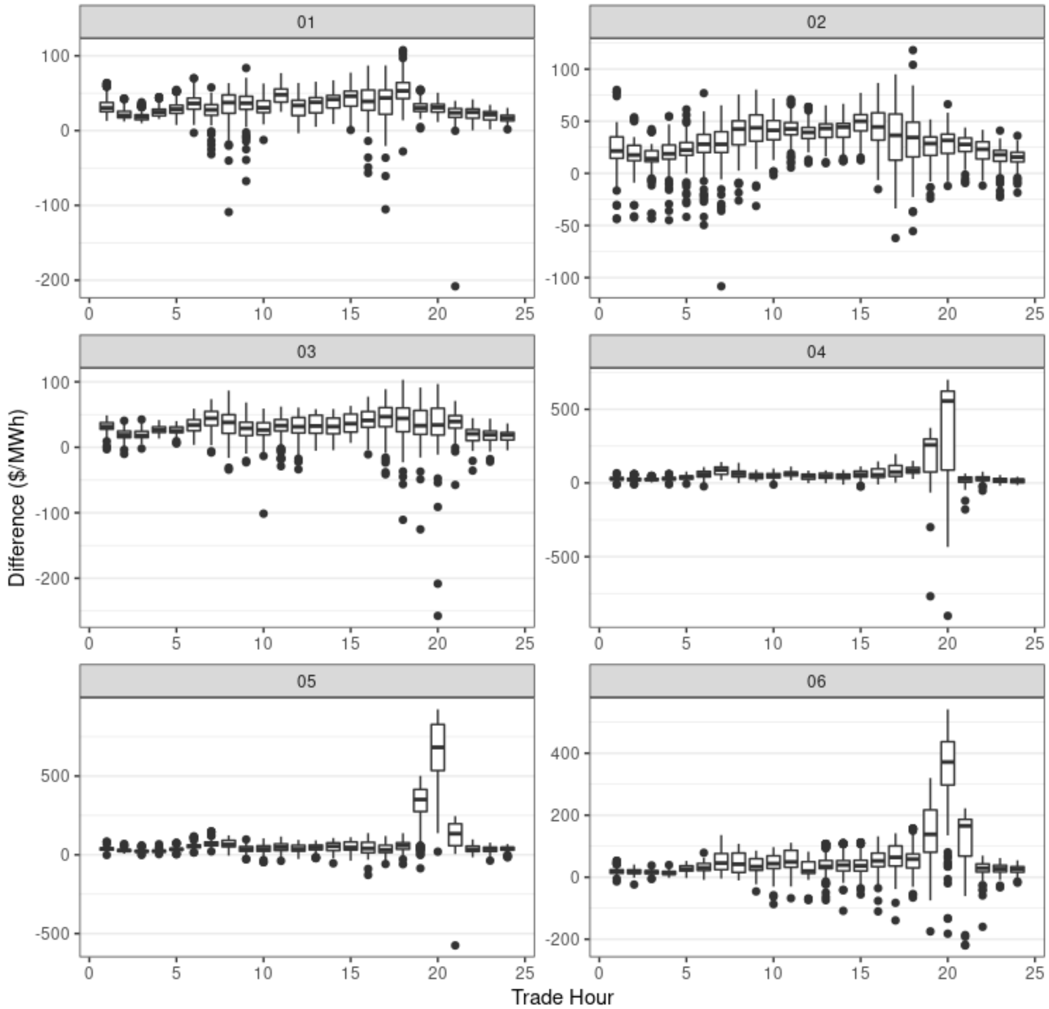


Figure 43. Hourly boxplot of scale, methodology 12: Linear, 97.5, 60/60, hourly

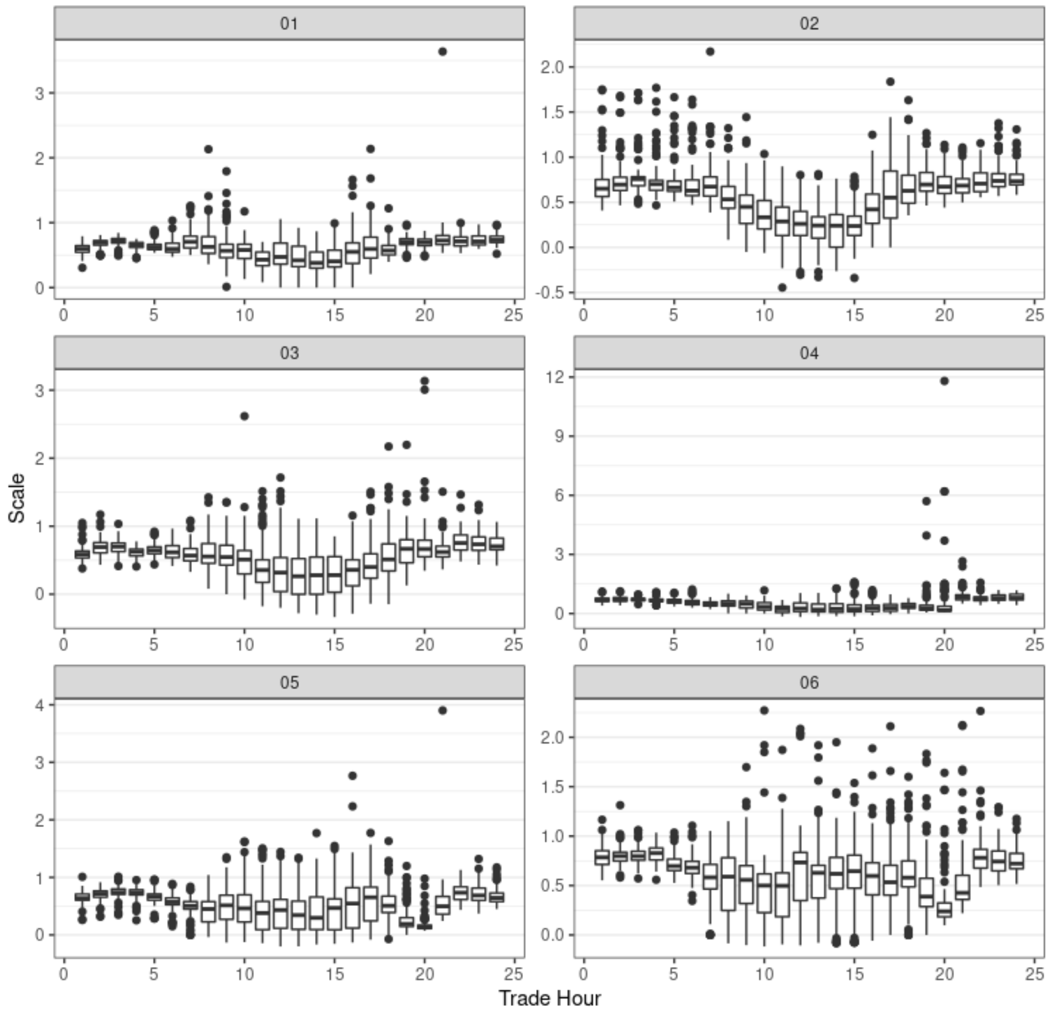


Table 19. Methodology 13: Linear, 97.5, 60/60, hourly, weekend distinction

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.65%	30.19	29.27	0.64
February 2022	94.46%	31.33	29.48	0.58
March 2022	95.29%	31.62	29.76	0.57
April 2022	95.80%	66.87	63.20	0.53
May 2022	95.50%	81.49	79.54	0.53
June 2022	93.37%	57.79	53.67	0.63

Figure 44. Hourly boxplot of difference, methodology 13: Linear, 97.5, 60/60, hourly, weekend distinction

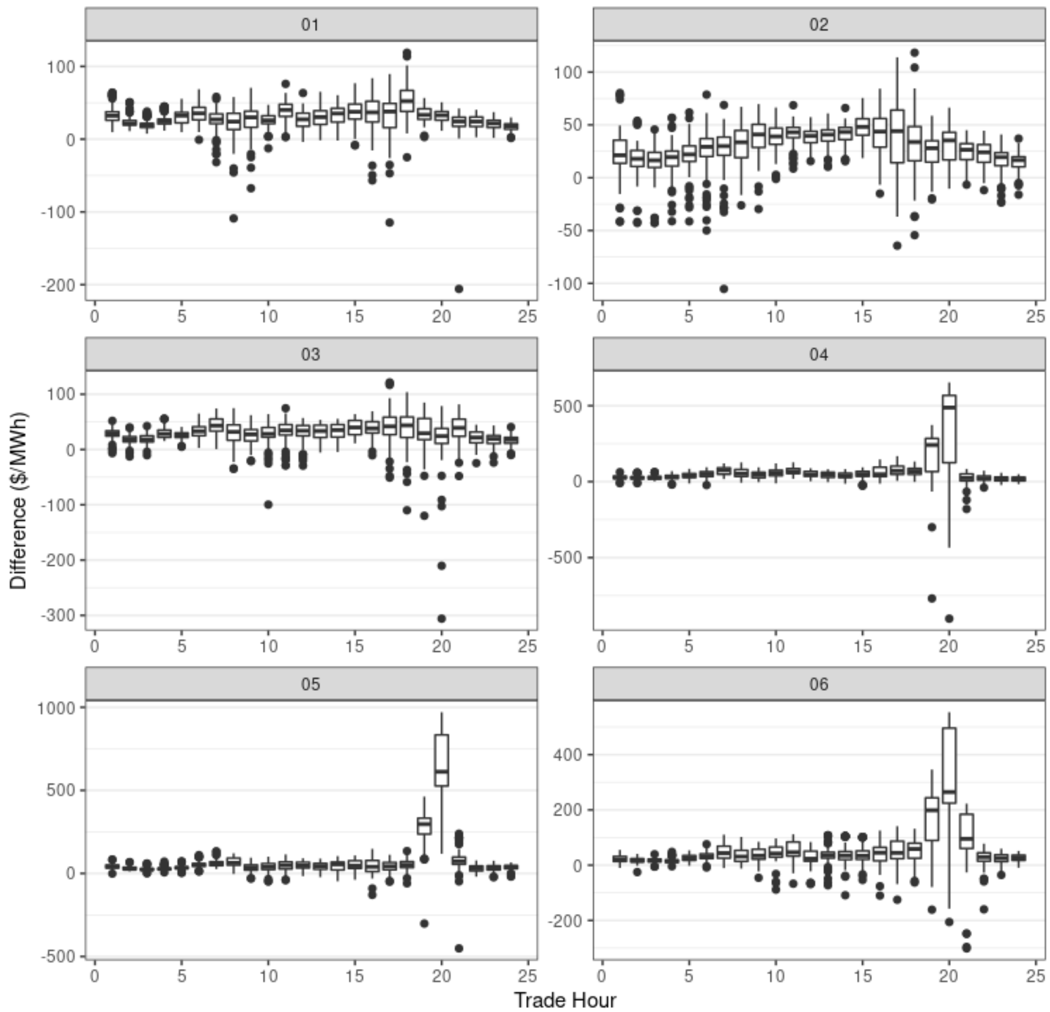


Figure 45. Hourly boxplot of scale, methodology 13: Linear, 97.5, 60/60, hourly, weekend distinction

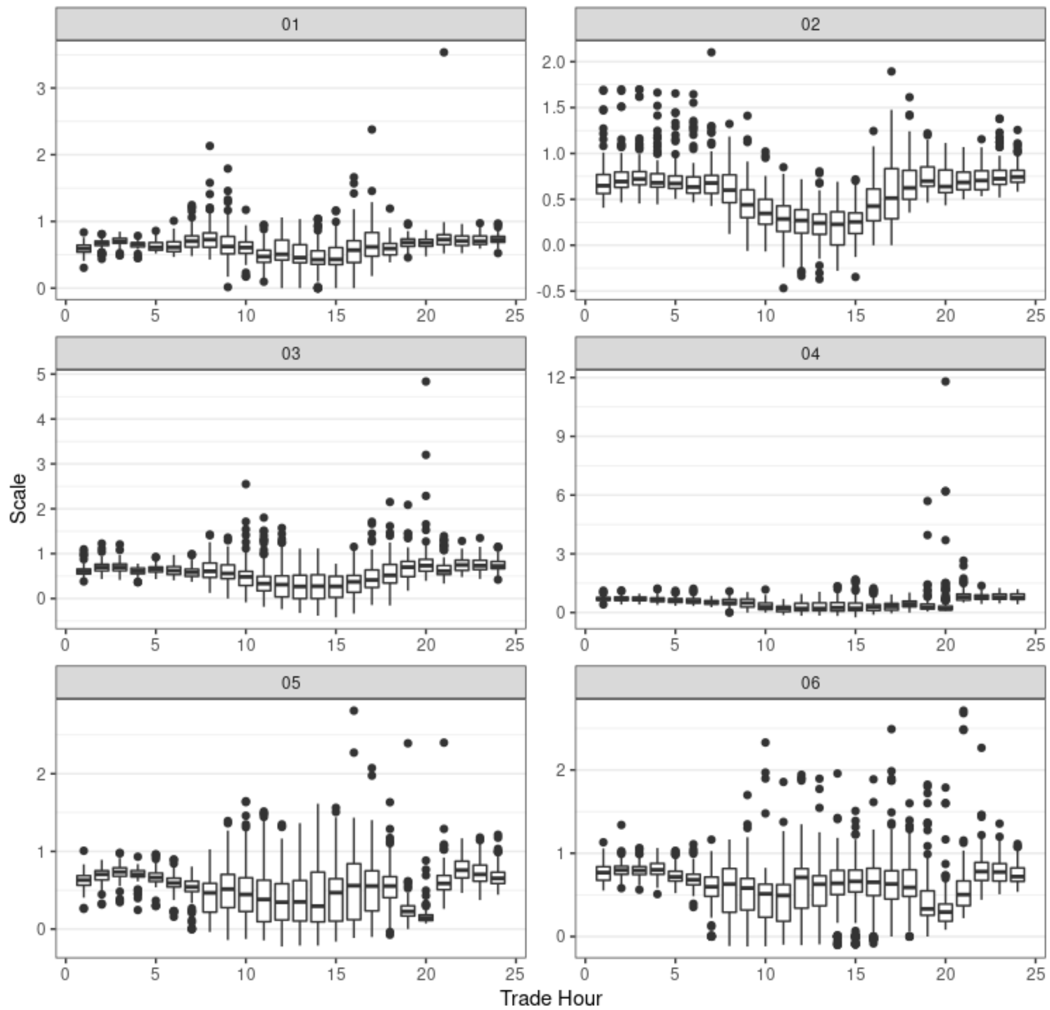


Table 20. Methodology 14: Linear, 90, 60/60, hourly

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	89.82%	16.43	14.11	0.78
February 2022	87.98%	20.39	16.80	0.70
March 2022	87.15%	19.93	16.54	0.69
April 2022	89.41%	31.75	25.83	0.66
May 2022	92.64%	37.13	32.93	0.64
June 2022	85.14%	29.80	21.66	0.77

Figure 46. Hourly boxplot of difference, methodology 14: Linear, 90, 60/60, hourly

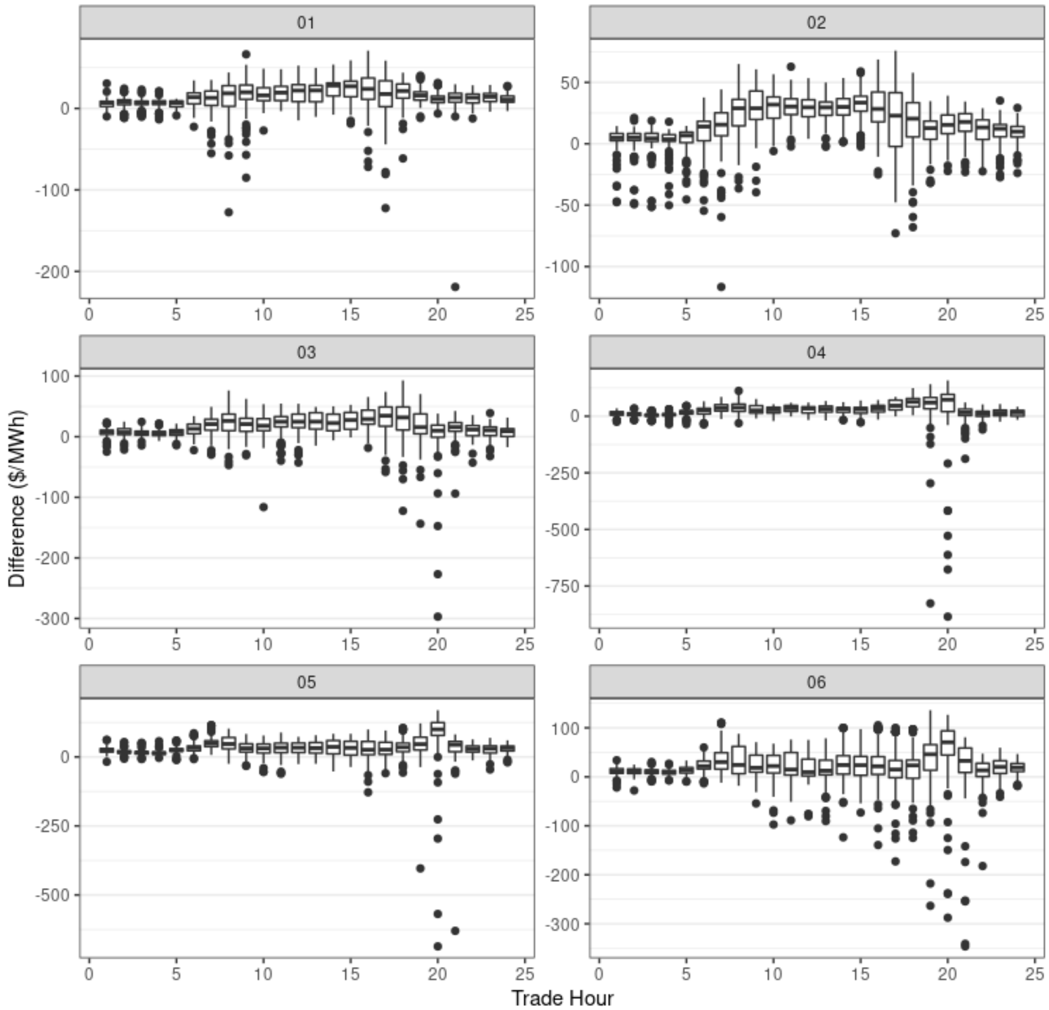


Figure 47. Hourly boxplot of scale, methodology 14: Linear, 90, 60/60, hourly

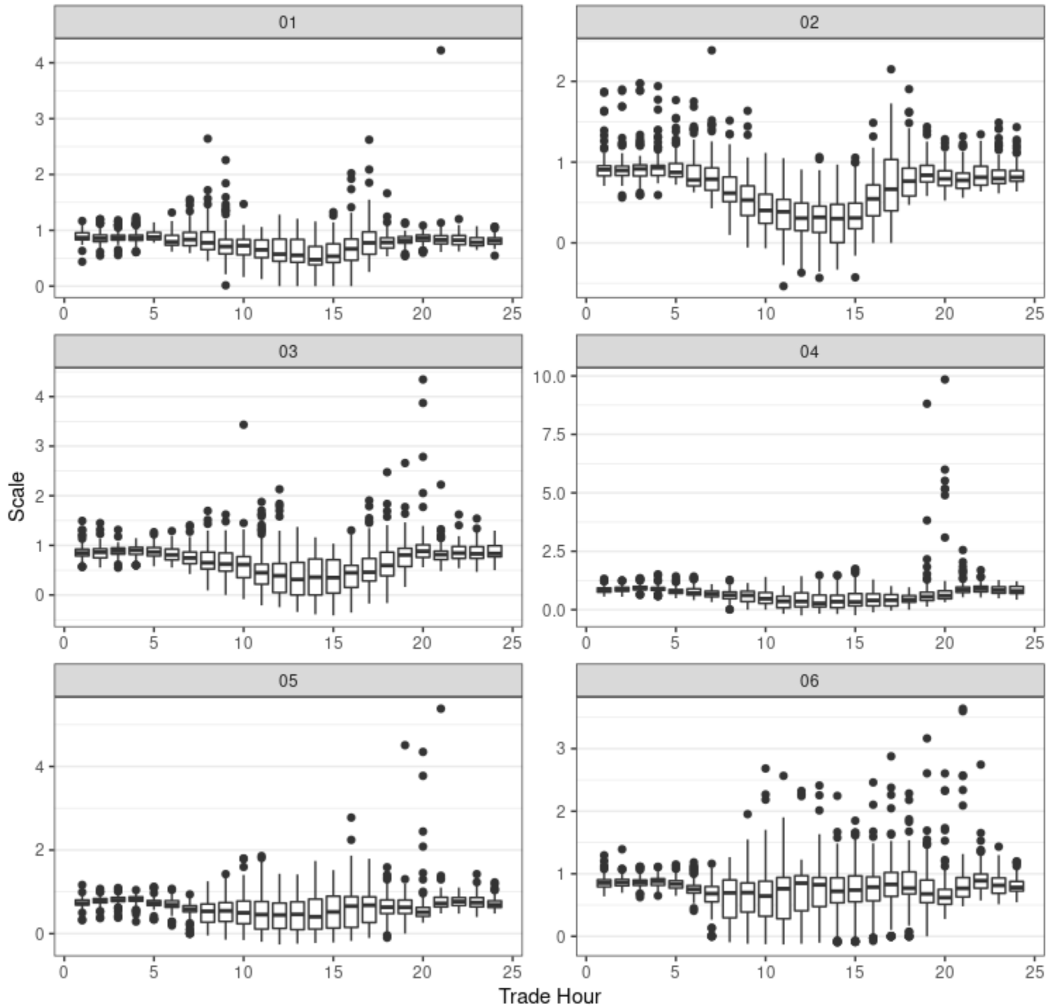


Table 21. Methodology 15: Linear, 90, 60/60, 1.2 scalar, hourly

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.95%	28.26	27.31	0.65
February 2022	95.35%	30.54	29.00	0.58
March 2022	96.33%	29.90	28.31	0.58
April 2022	96.98%	46.36	42.27	0.55
May 2022	97.25%	54.63	51.98	0.53
June 2022	94.41%	45.01	40.27	0.64

Figure 48. Hourly boxplot of difference, methodology 15: Linear, 90, 60/60, 1.2 scalar, hourly

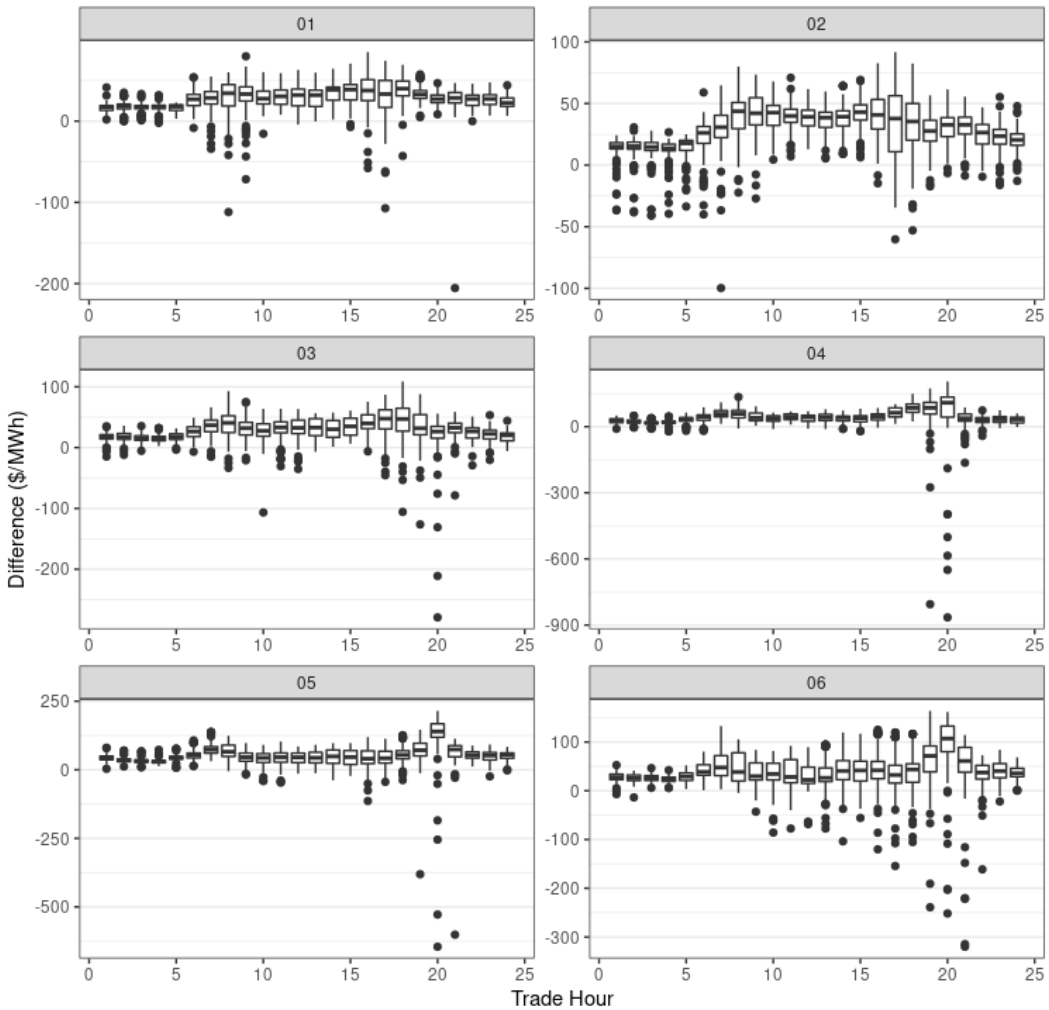


Figure 49. Hourly boxplot of scale, methodology 15: Linear, 90, 60/60, 1.2 scalar, hourly

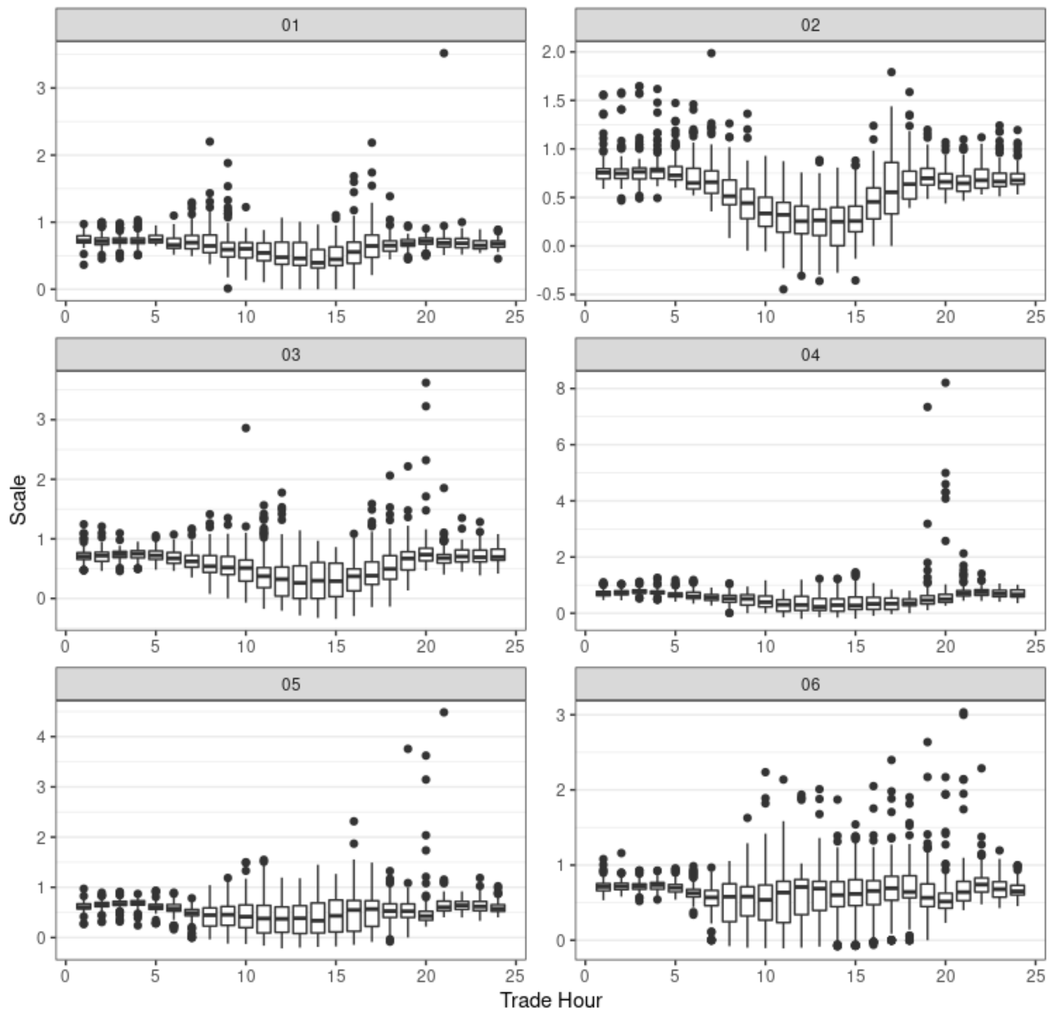


Table 22. Methodology 16: Linear, 90, 60/60, hourly, weekend distinction

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	89.38%	16.14	13.67	0.78
February 2022	87.84%	19.87	16.37	0.70
March 2022	86.68%	19.30	15.74	0.70
April 2022	89.17%	29.34	23.27	0.67
May 2022	91.80%	35.60	31.05	0.64
June 2022	85.21%	28.83	21.04	0.77

Figure 50. Hourly boxplot of difference, methodology 16: Linear, 90, 60/60, hourly, weekend distinction

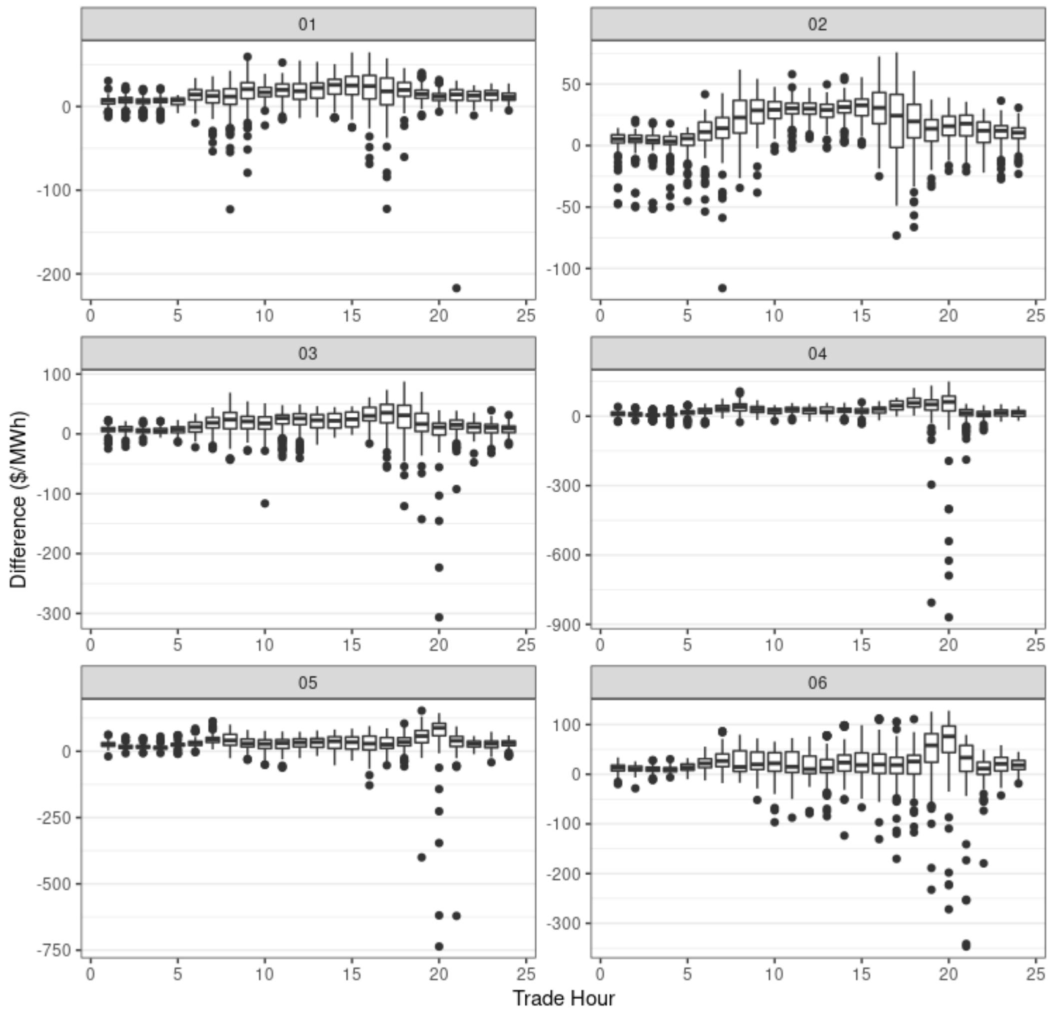


Figure 51. Hourly boxplot of scale, methodology 16: Linear, 90, 60/60, hourly, weekend distinction

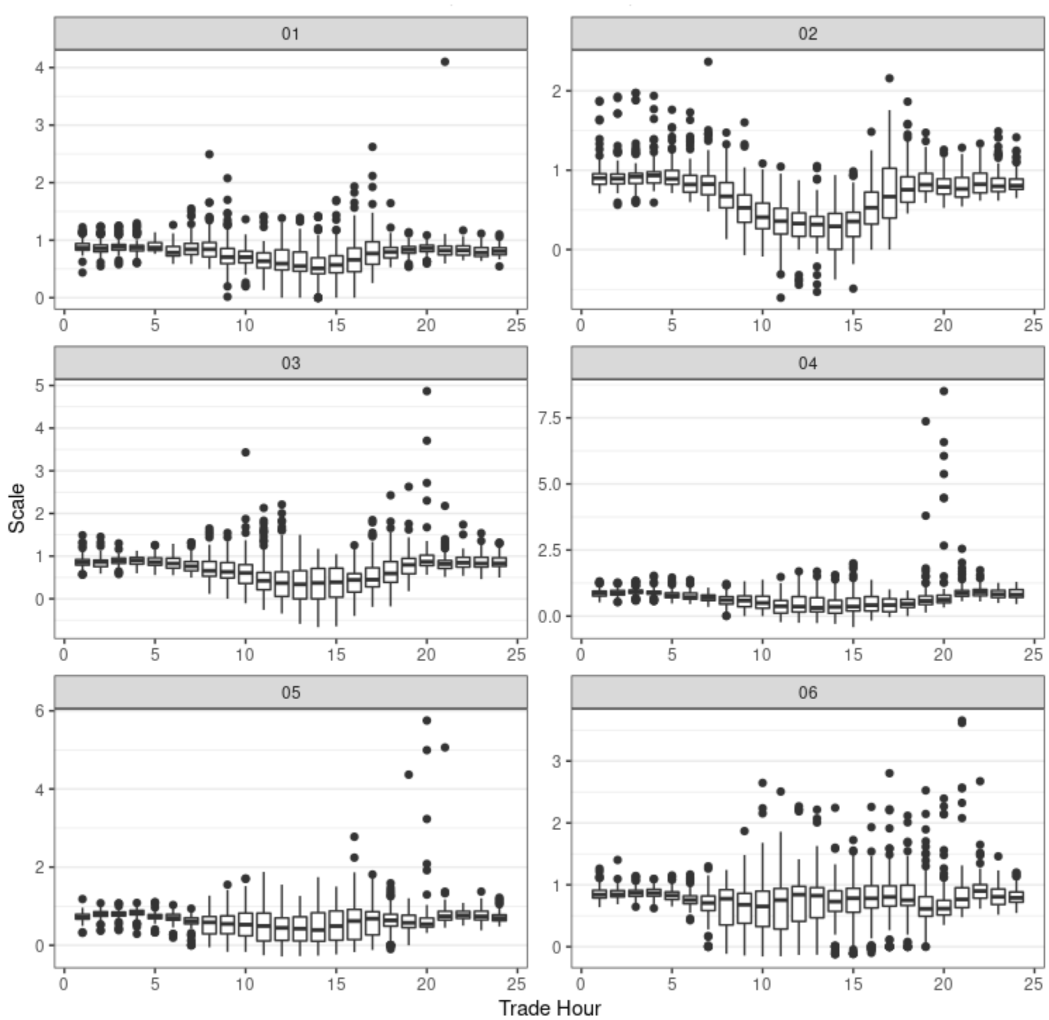


Table 23. Methodology 17: Quadratic, 97.5, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	99.16%	40.39	39.90	0.58
February 2022	95.69%	37.69	36.49	0.54
March 2022	97.44%	37.54	36.33	0.53
April 2022	95.07%	94.18	90.68	0.53
May 2022	92.98%	59.39	54.86	0.60
June 2022	95.38%	61.64	57.99	0.60

Figure 52. Hourly boxplot of difference, methodology 17: Quadratic, 97.5, 60/60, 15 min

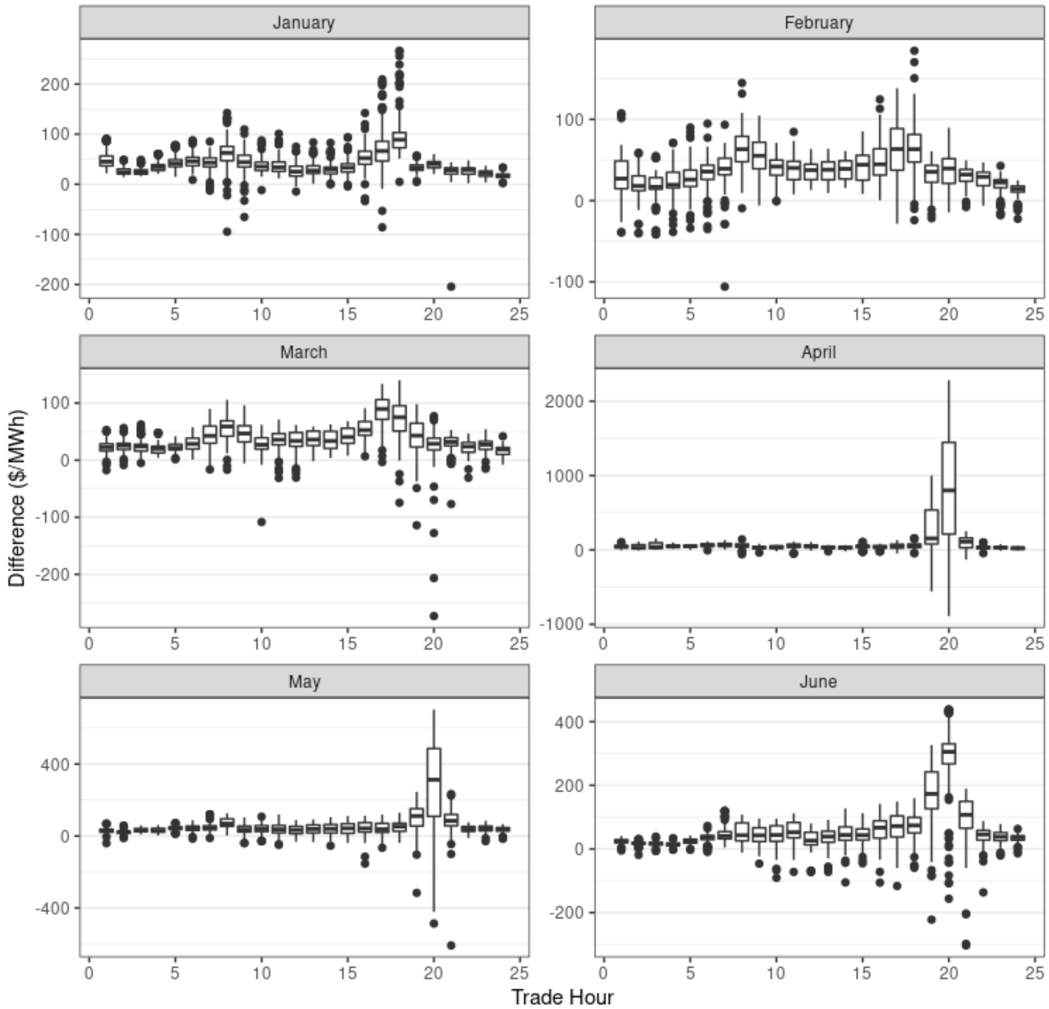


Figure 53. Hourly boxplot of scale, methodology 17: Quadratic, 97.5, 60/60, 15 min

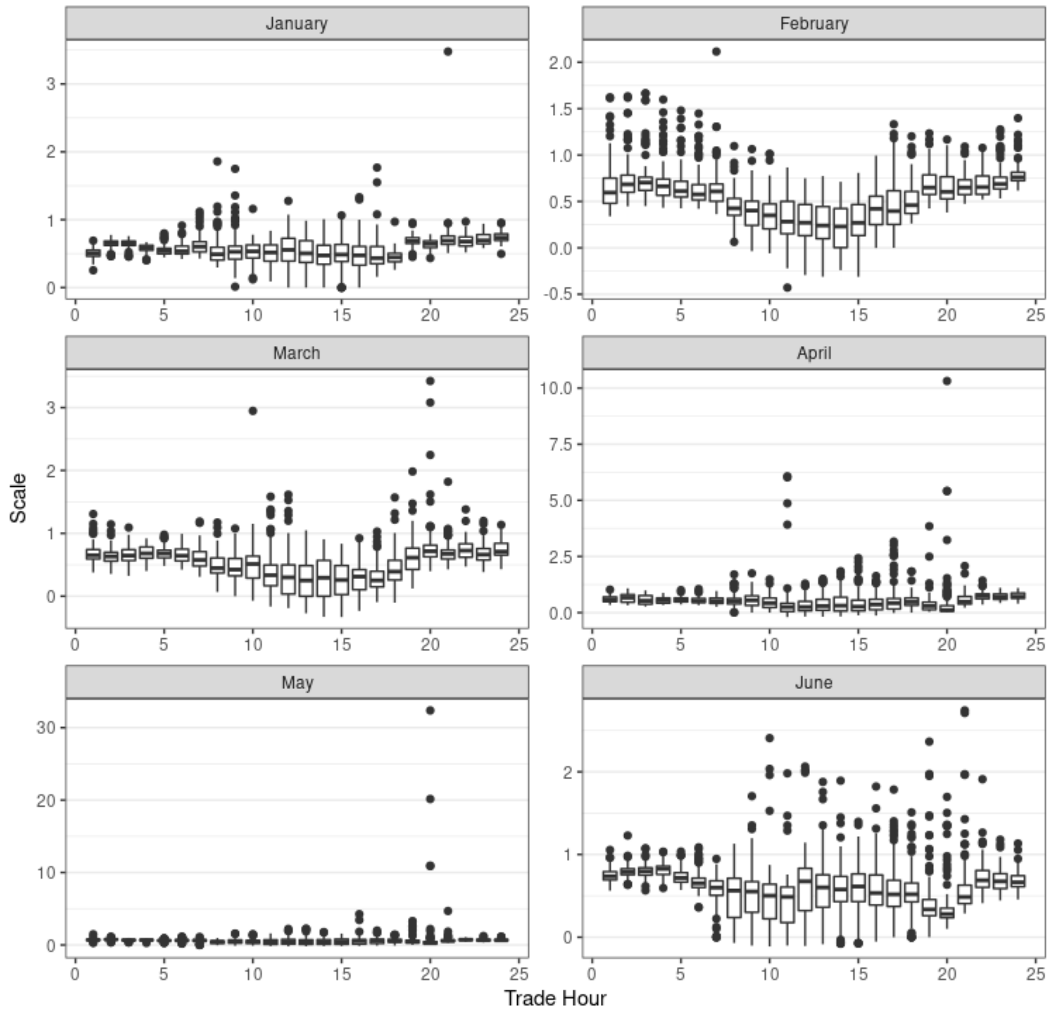


Table 24. Methodology 18: Quadratic, 90, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	92.04%	17.61	15.90	0.77
February 2022	89.58%	21.22	18.40	0.69
March 2022	90.14%	22.85	20.12	0.66
April 2022	87.88%	35.46	29.05	0.68
May 2022	87.50%	33.66	26.77	0.69
June 2022	87.22%	30.87	23.20	0.75

Figure 54. Hourly boxplot of difference, methodology 18: Quadratic, 90, 60/60, 15 min

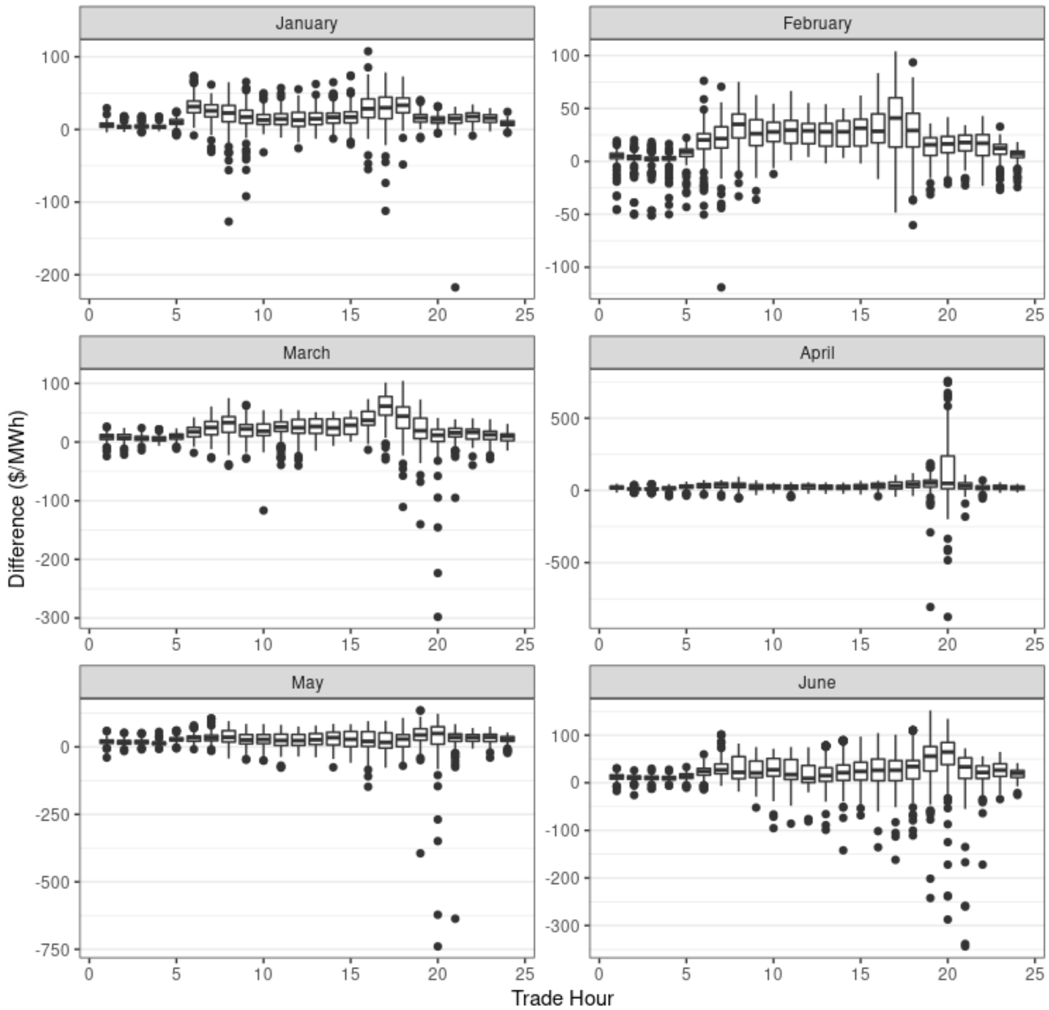


Figure 55. Hourly boxplot of scale, methodology 18: Quadratic, 90, 60/60, 15 min

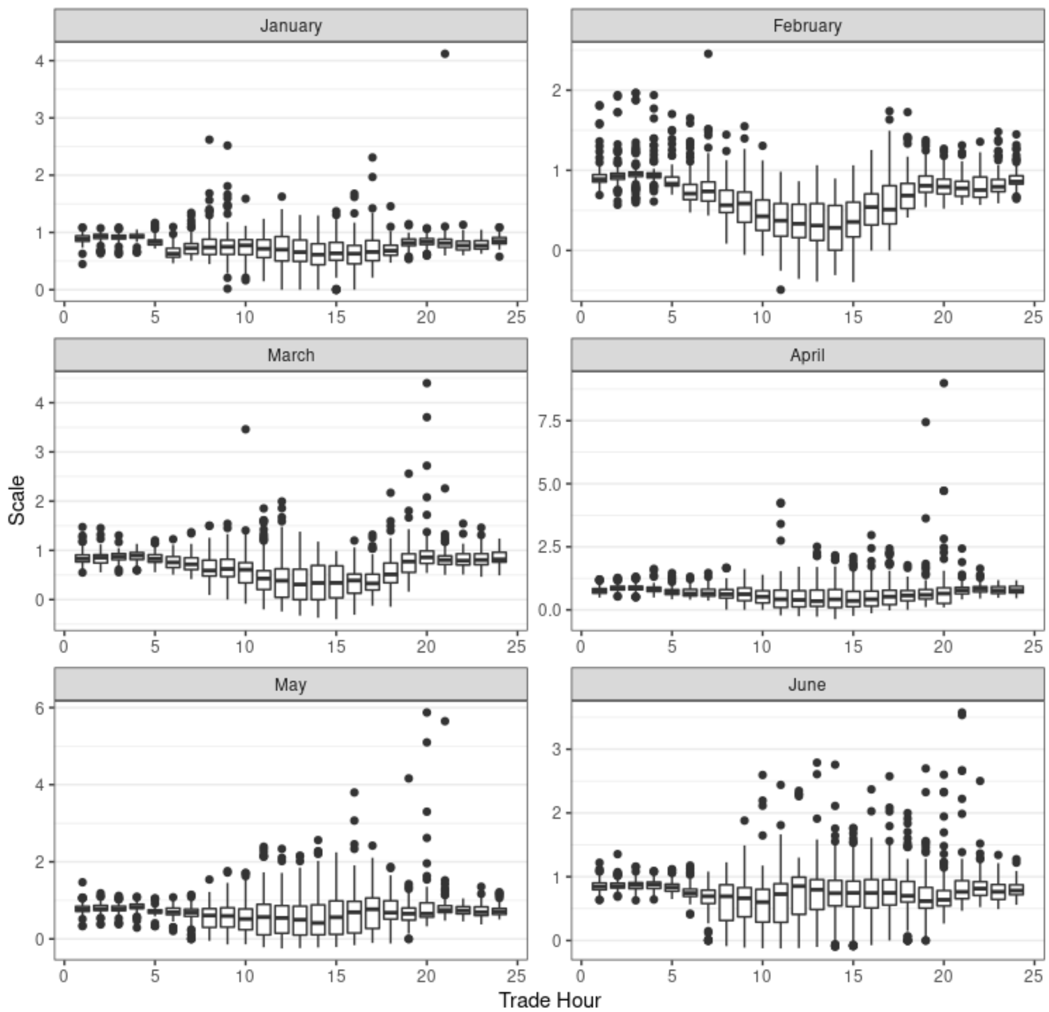


Table 25. Methodology 19: Daily cap, linear, 90, 60/60, 15 min, 1.2 scalar

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	98.89%	53.40	52.77	0.50
February 2022	96.88%	48.05	47.08	0.48
March 2022	97.91%	54.82	53.54	0.44
April 2022	98.92%	97.40	93.60	0.38
May 2022	99.53%	128.19	126.08	0.33
June 2022	98.44%	113.47	110.90	0.39

Figure 56. Hourly boxplot of difference, methodology 19: Daily cap, linear, 90, 60/60, 15 min, 1.2 scalar

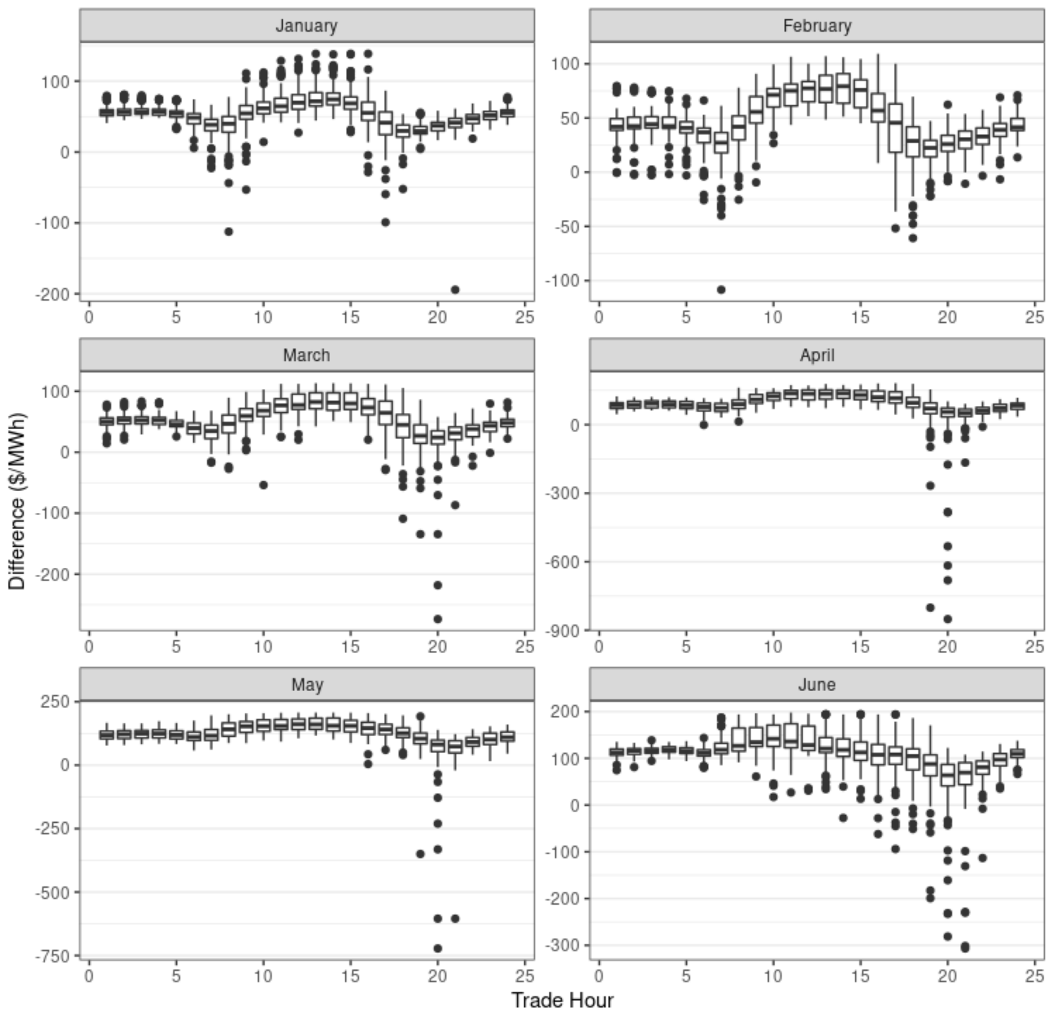
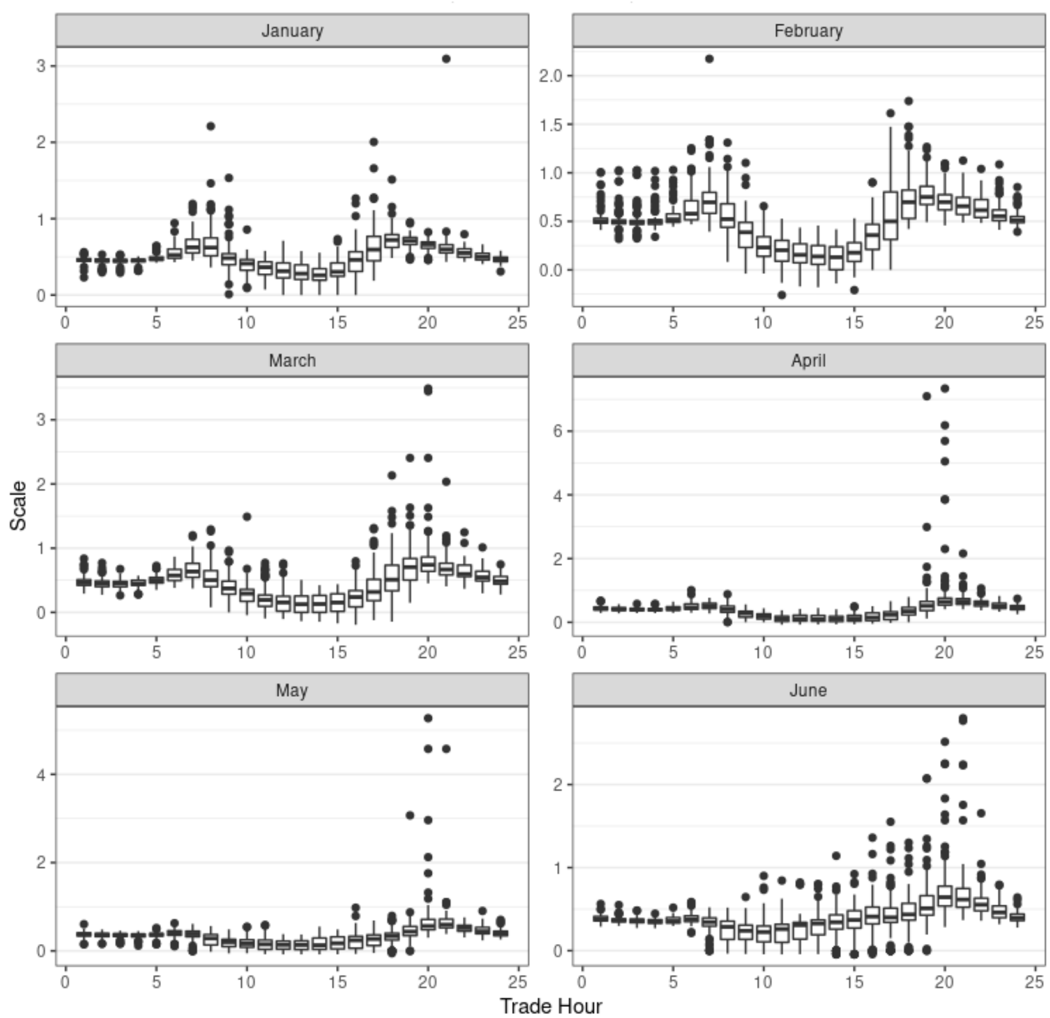


Figure 57. Hourly boxplot of scale, methodology 19: Daily cap, linear, 90, 60/60, 15 min, 1.2 scalar



Methodologies 20 - 22: FMM LMPs vs SoCal Citygate Gas Price

Table 26. Methodology 20: Linear, 97.5, 30/30, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	96.24%	27.90	27.05	0.68
February 2022	95.50%	32.05	30.93	0.58
March 2022	96.57%	34.81	33.53	0.55
April 2022	96.29%	71.35	67.61	0.54
May 2022	96.47%	59.32	56.63	0.55

June 2022	95.59%	79.86	77.35	0.59

Figure 58. Hourly boxplot of difference, methodology 20: Linear, 97.5, 30/30, 15 min

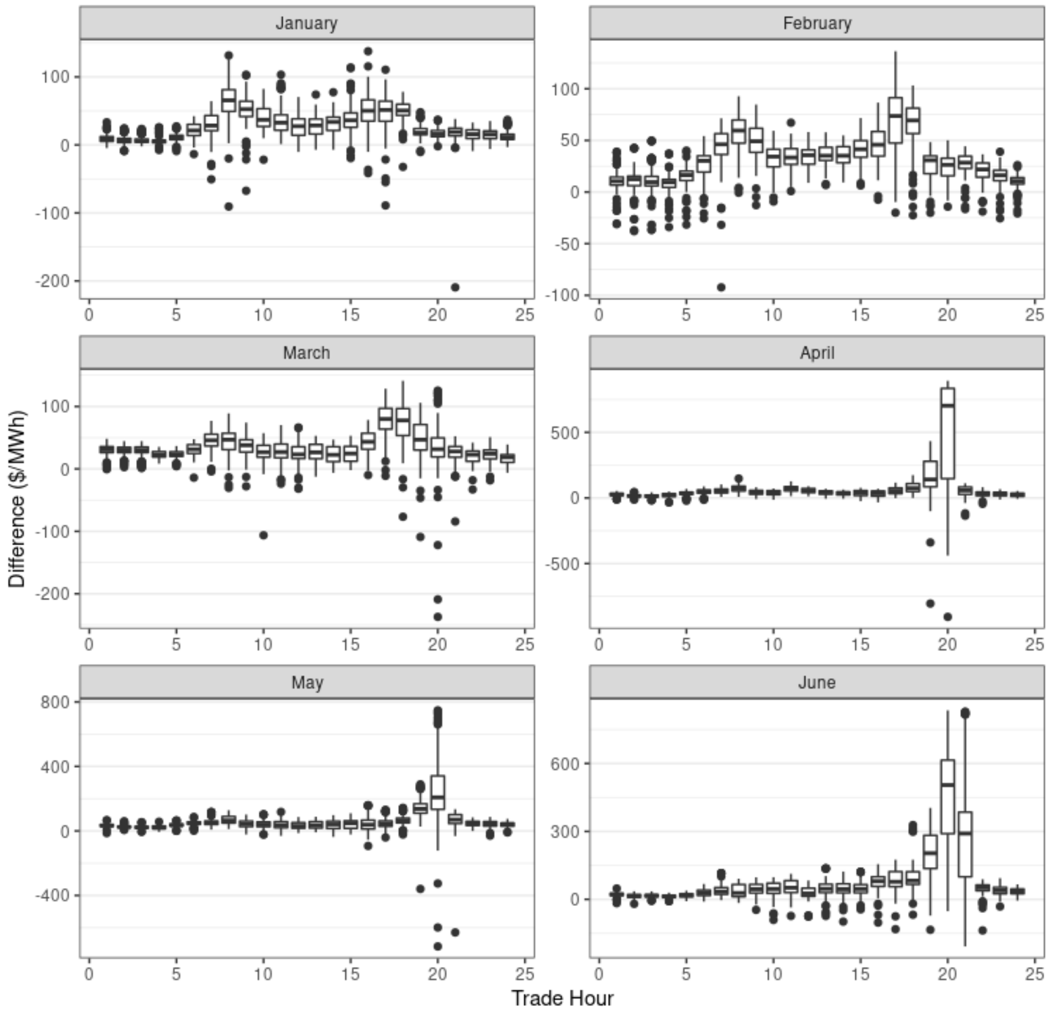


Figure 59. Hourly boxplot of scale, methodology 20: Linear, 97.5, 30/30, 15 min

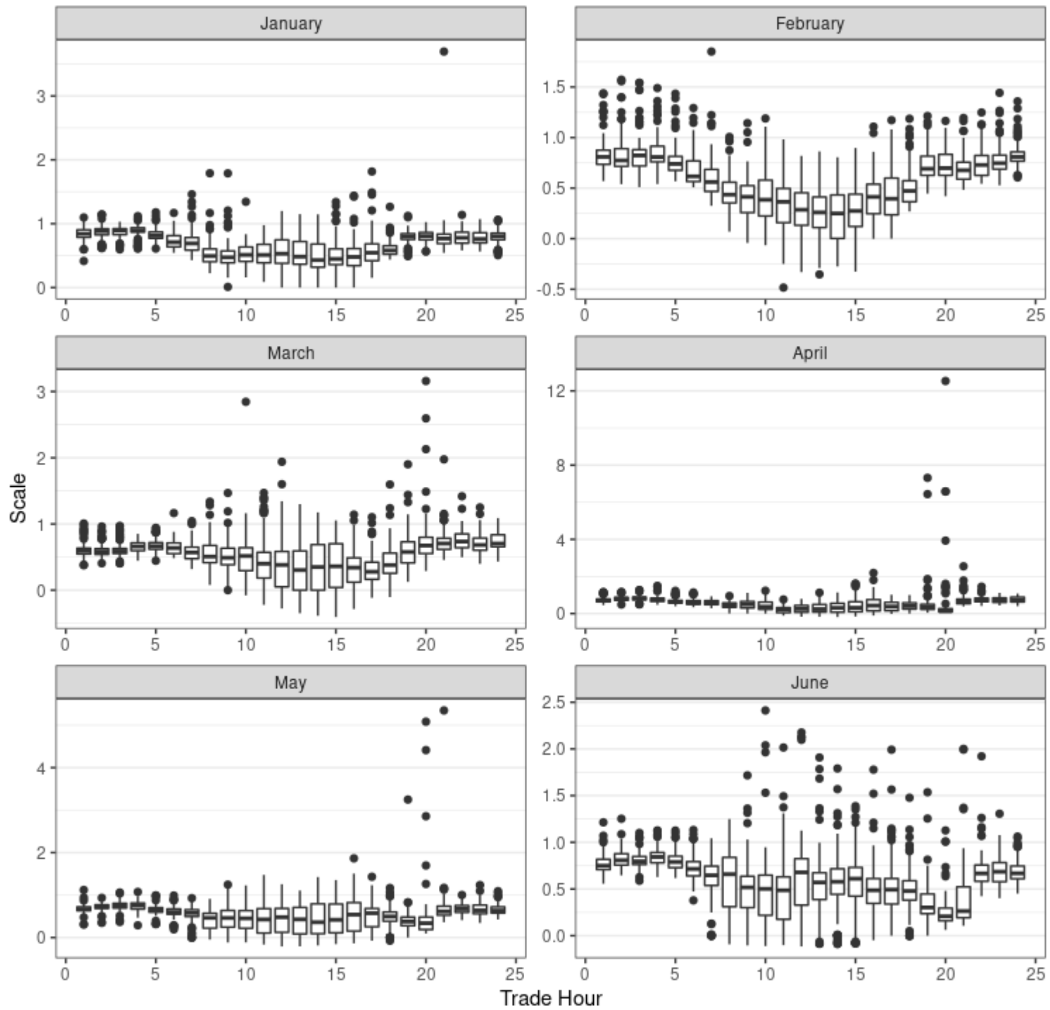


Table 27. Methodology 21: Linear, 97.5, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	98.69%	30.34	29.73	0.65
February 2022	95.69%	33.84	32.55	0.57
March 2022	96.87%	33.82	32.48	0.56
April 2022	97.64%	71.83	68.64	0.50
May 2022	98.52%	88.22	87.25	0.50
June 2022	95.97%	70.24	67.10	0.59

Figure 60. Hourly boxplot of difference, methodology 21: Linear, 97.5, 60/60, 15 min

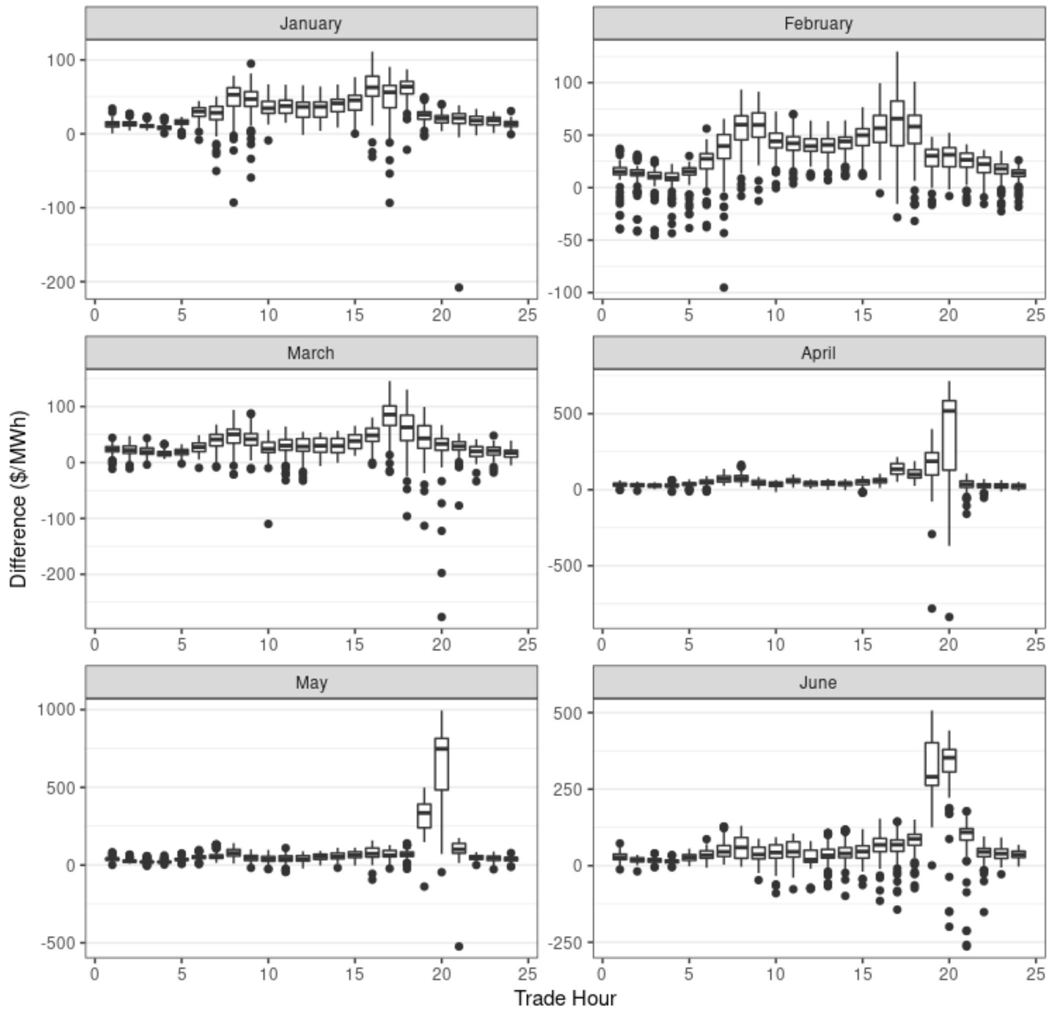


Figure 61. Hourly boxplot of scale, methodology 21: Linear, 97.5, 60/60, 15 min

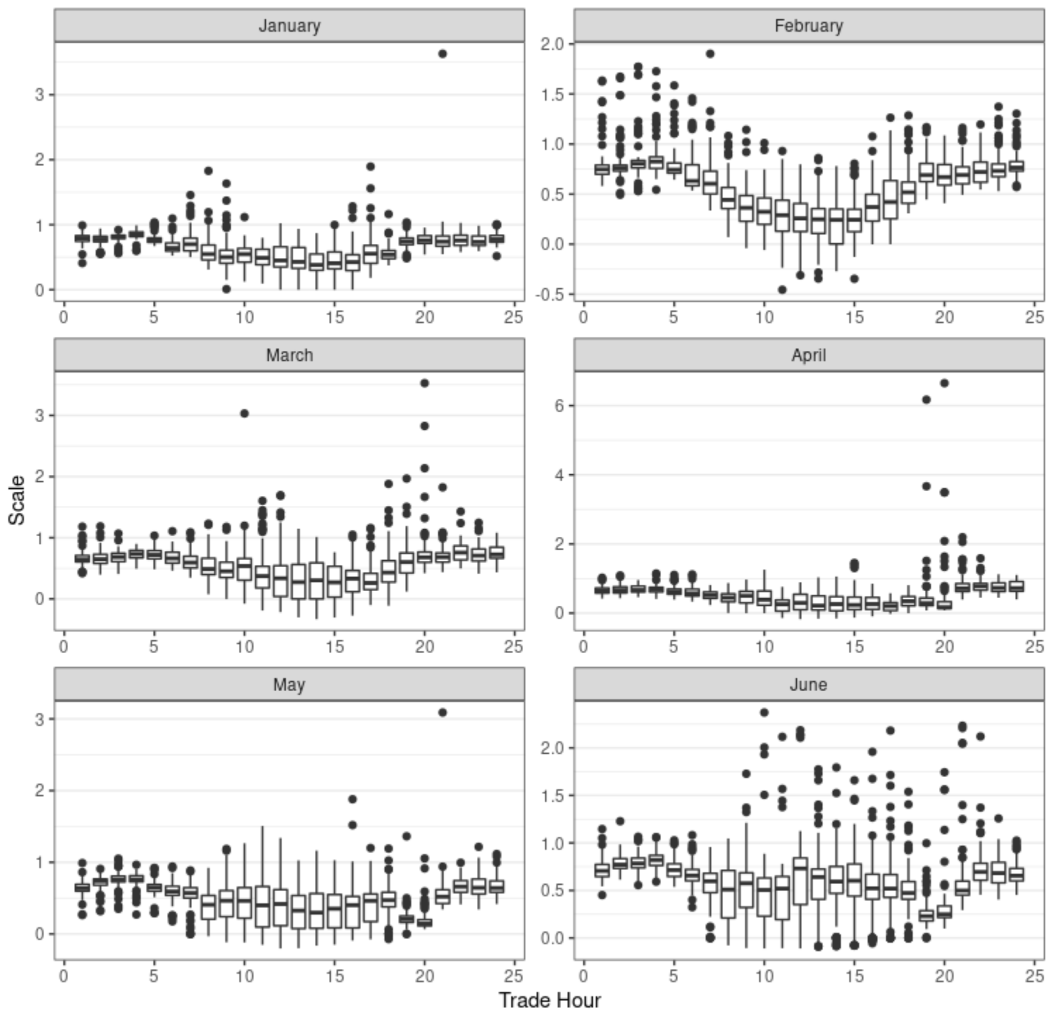


Table 28. Methodology 22: Linear, 90, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	88.84%	17.38	15.04	0.77
February 2022	87.50%	21.04	17.64	0.69
March 2022	86.00%	19.87	16.44	0.70
April 2022	89.76%	33.00	27.24	0.65
May 2022	94.66%	37.78	34.34	0.62
June 2022	86.01%	31.82	24.49	0.75

Figure 62. Hourly boxplot of difference, methodology 22: Linear, 90, 60/60, 15 min

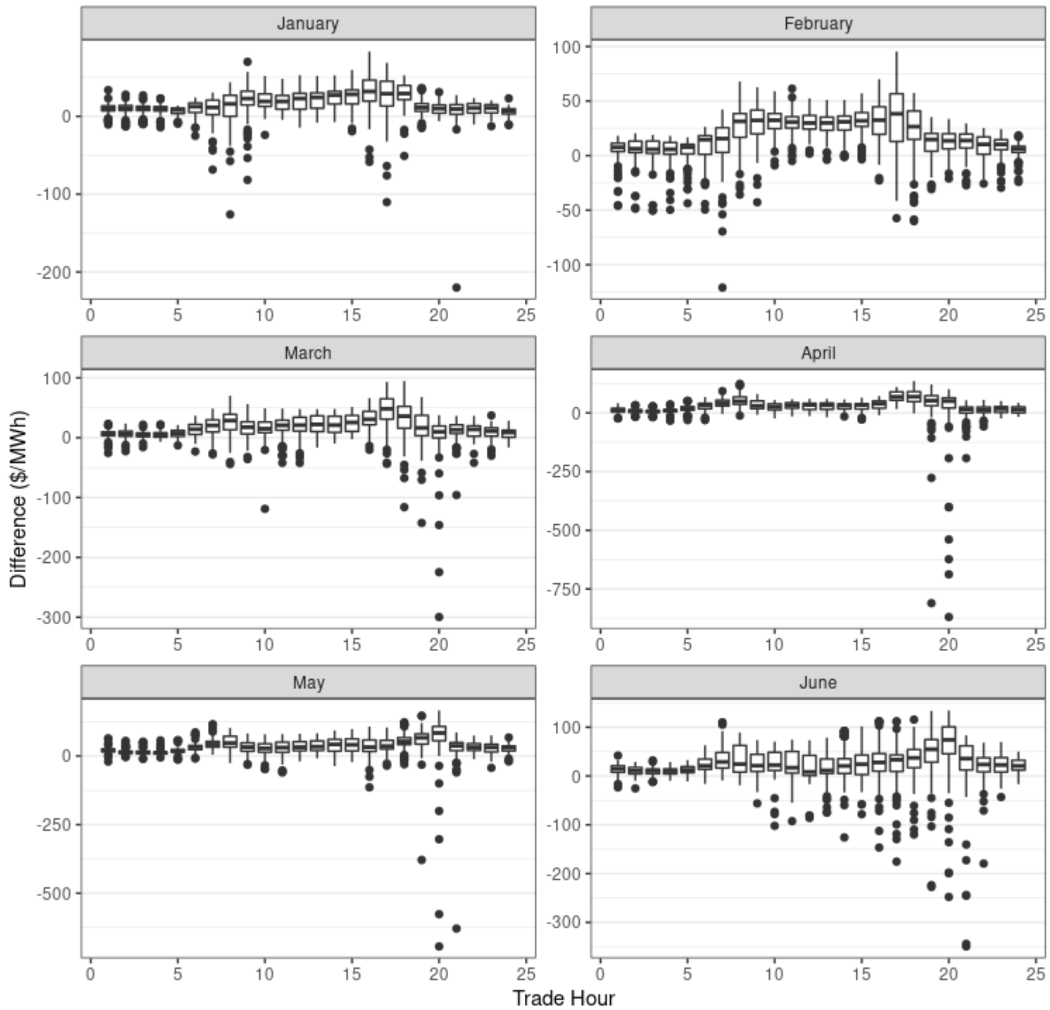
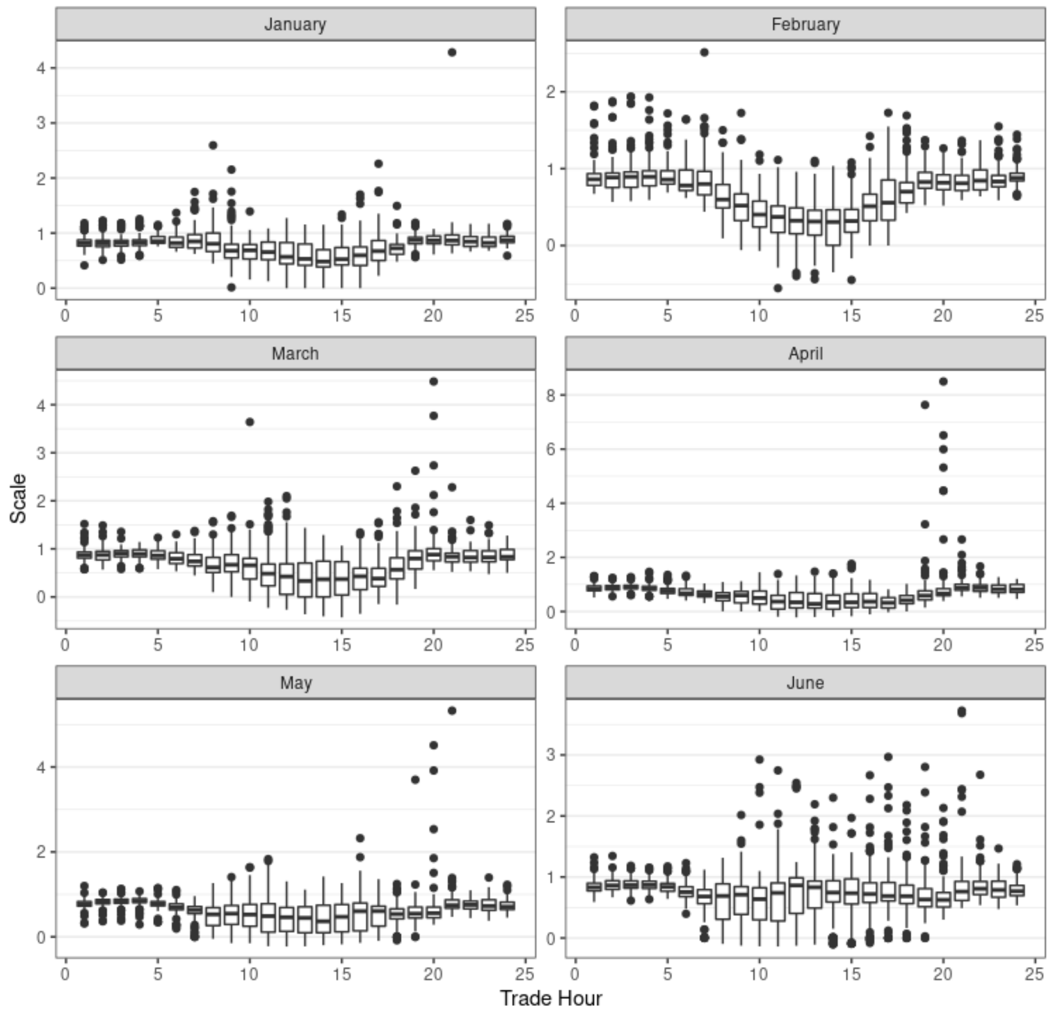


Figure 63. Hourly boxplot of scale, methodology 22: Linear, 90, 60/60, 15 min



Methodologies 23 - 25: FMM LMPs vs Net Load

Table 29. Methodology 23: Linear, 97.5, 30/30, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	96.62%	136.14	135.48	0.48
February 2022	95.85%	166.67	166.00	0.38
March 2022	92.39%	23.42	21.55	0.67
April 2022	84.06%	29.41	25.12	0.66
May 2022	91.72%	36.78	33.17	0.64

June 2022	95.99%	89.67	88.13	0.58

Figure 64. Hourly boxplot of difference, methodology 23: Linear, 97.5, 30/30, 15 min

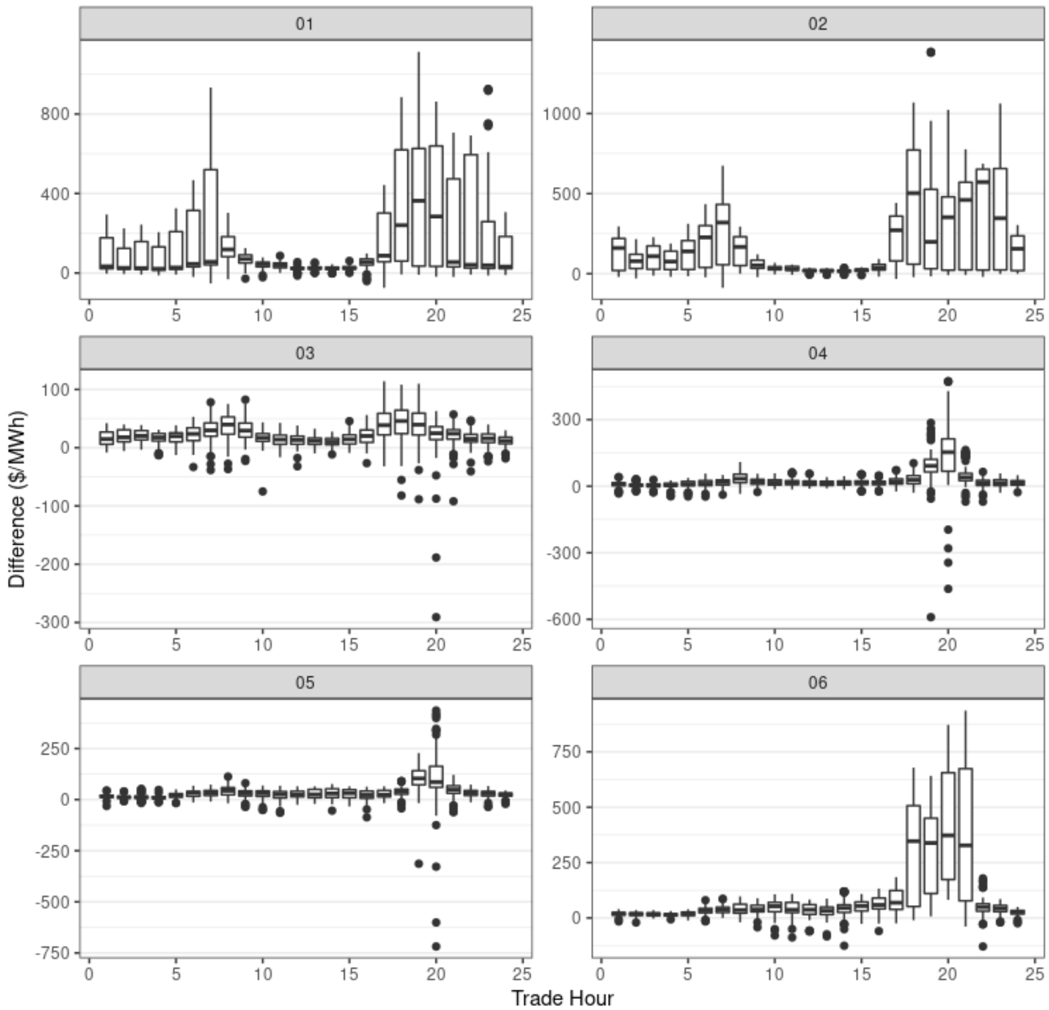


Figure 65. Hourly boxplot of scale, methodology 23: Linear, 97.5, 30/30, 15 min

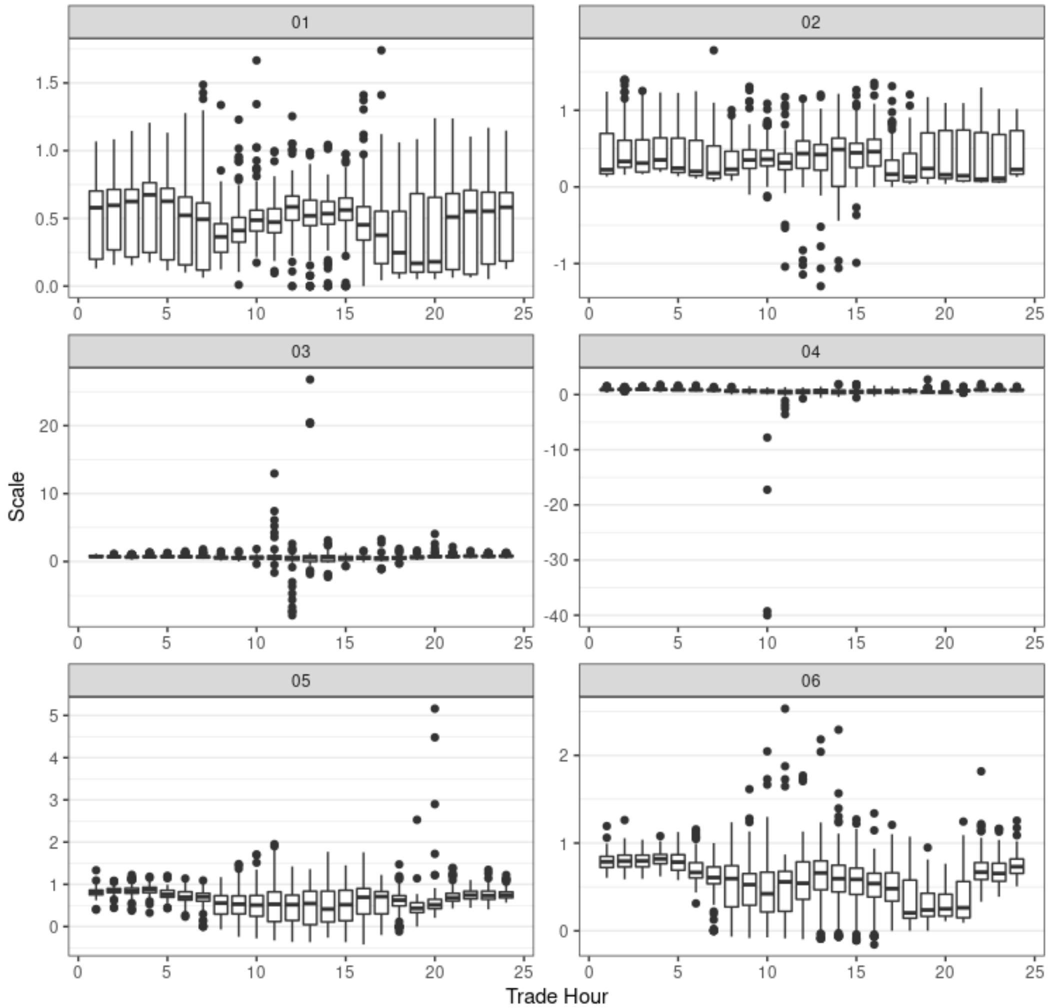


Table 30. Methodology 24: Linear, 97.5, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	99.63%	141.37	141.29	0.41
February 2022	97.95%	94.73	94.32	0.45
March 2022	91.75%	24.03	22.06	0.62
April 2022	78.88%	22.31	16.31	0.75
May 2022	89.82%	43.23	40.41	0.64
June 2022	95.04%	68.97	67.01	0.60

Figure 66. Hourly boxplot of difference, methodology 24: Linear, 97.5, 60/60, 15 min

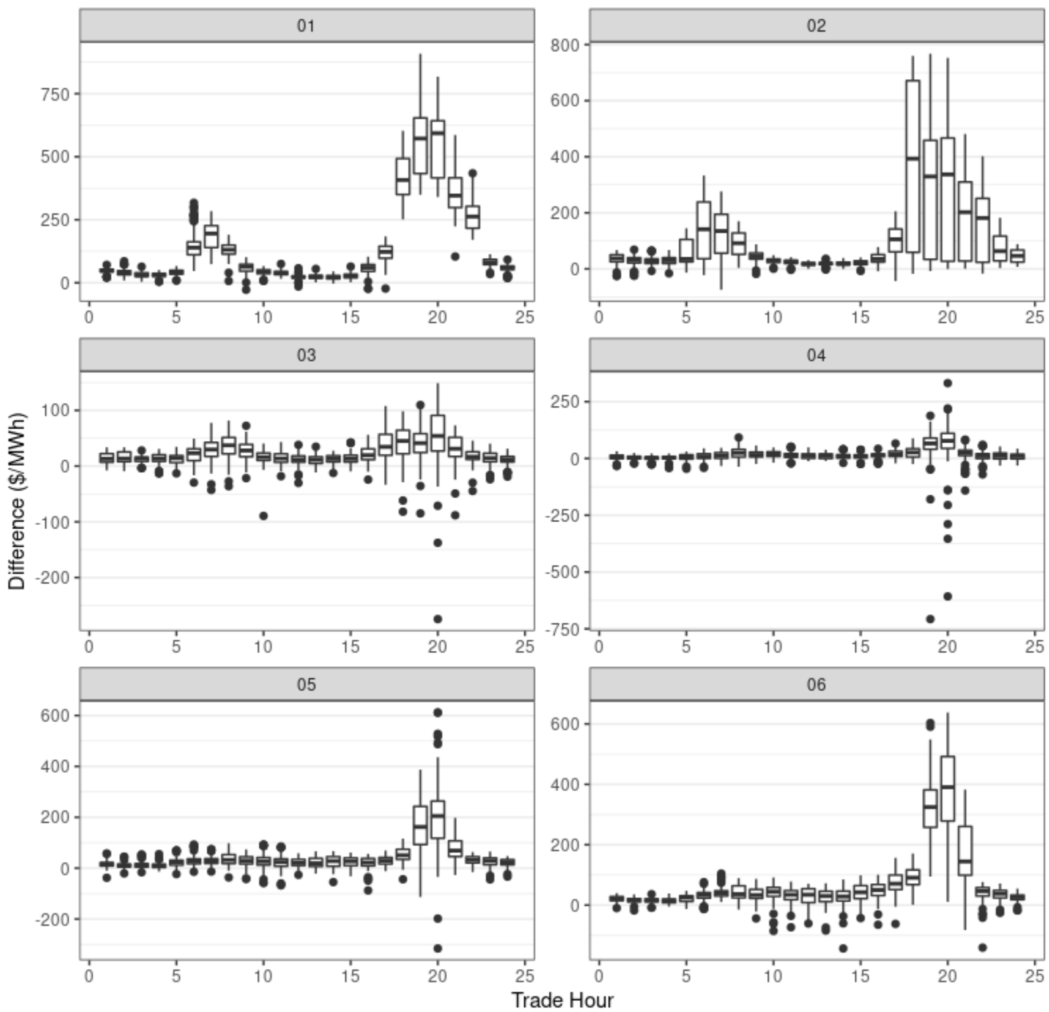


Figure 67. Hourly boxplot of scale, methodology 24: Linear, 97.5, 60/60, 15 min

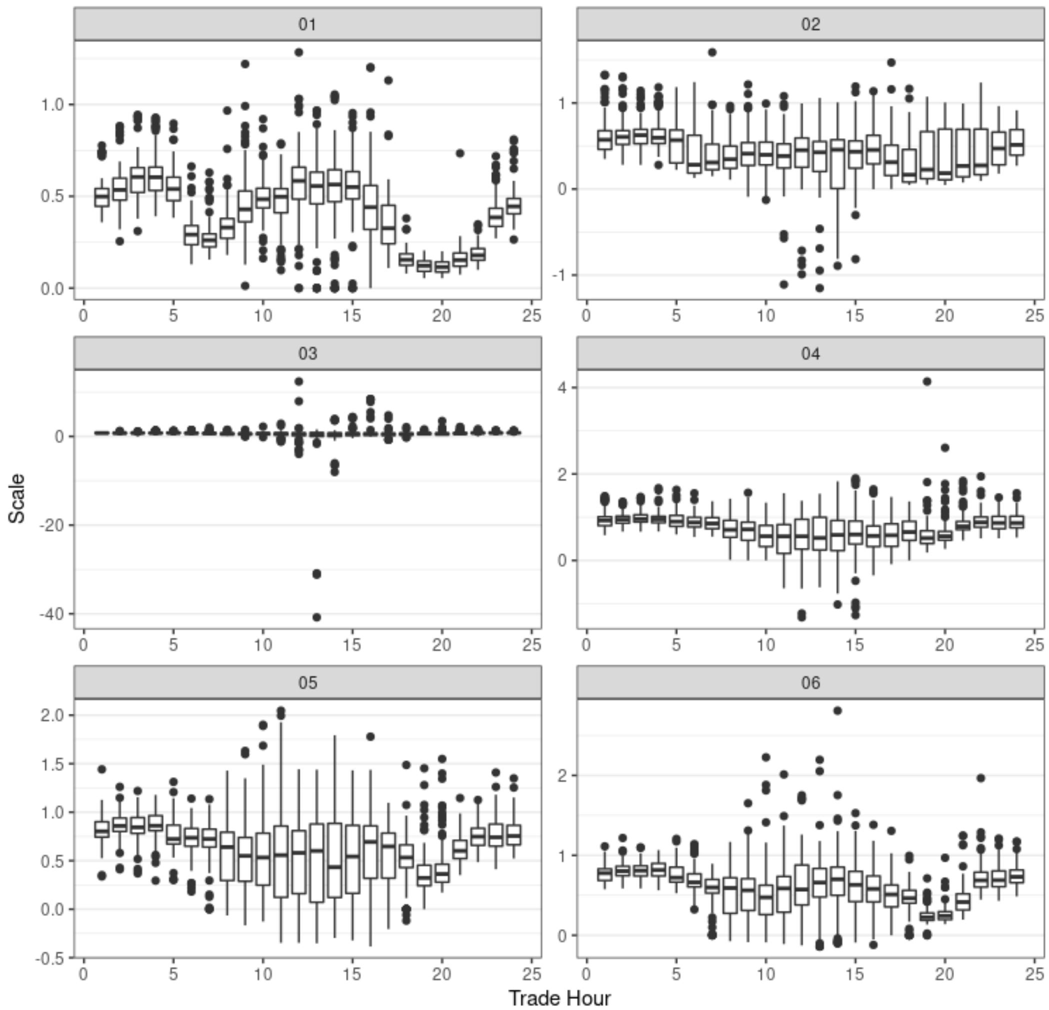


Table 31. Methodology 25: Linear, 90, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	92.53%	21.90	20.29	0.72
February 2022	90.51%	20.99	18.99	0.67
March 2022	76.53%	13.20	8.13	1.04
April 2022	44.51%	14.97	-3.70	0.99
May 2022	69.67%	20.34	10.21	0.82
June 2022	79.61%	28.33	20.73	0.78

Figure 68. Hourly boxplot of difference, methodology 25: Linear, 90, 60/60, 15 min

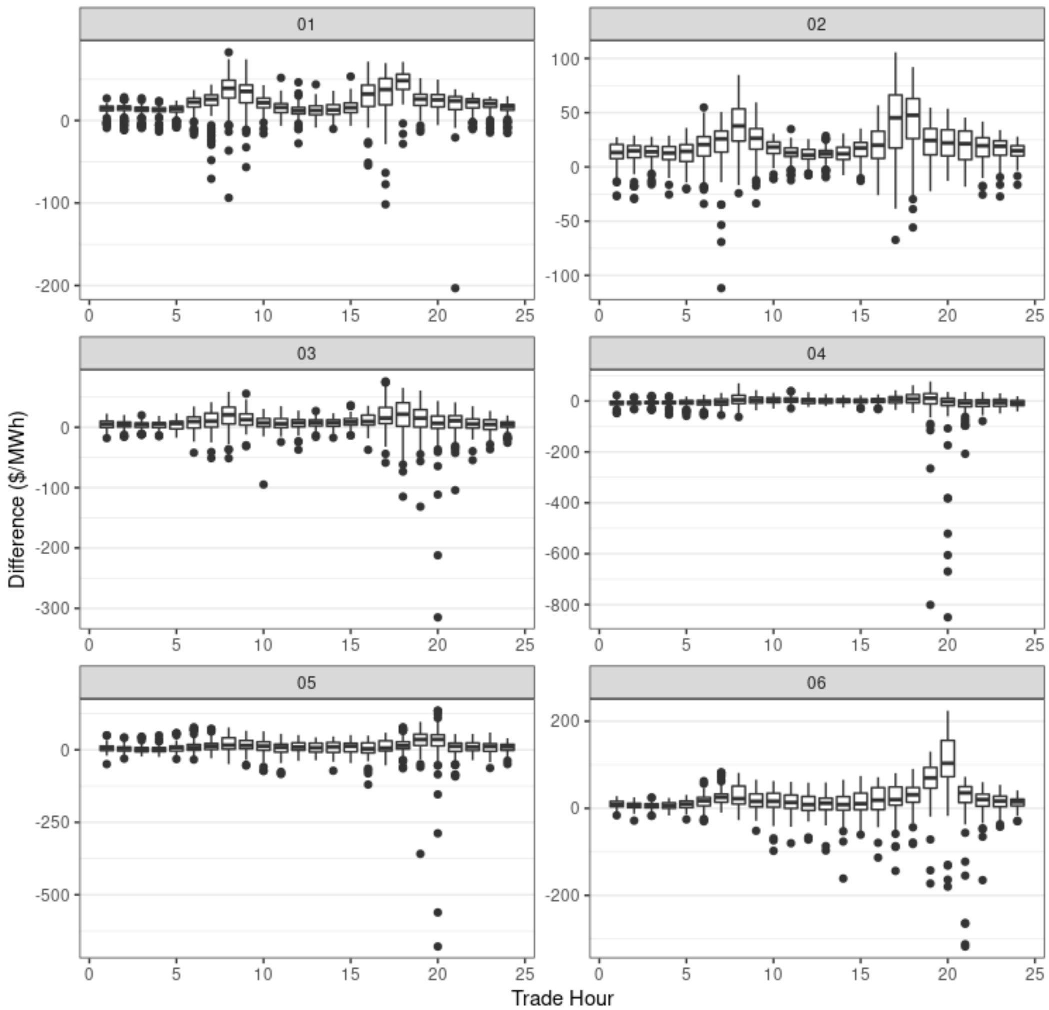
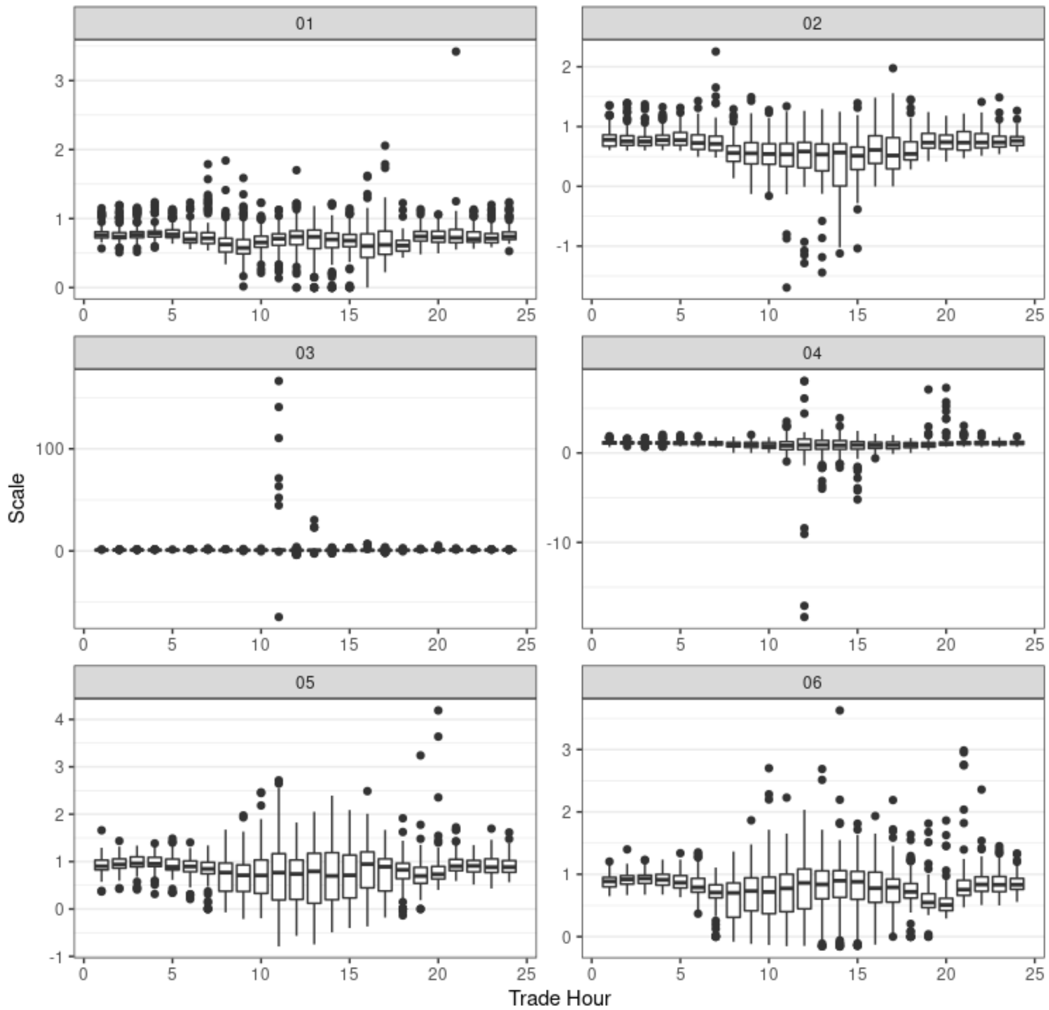


Figure 69. Hourly boxplot of scale, methodology 25: Linear, 90, 60/60, 15 min



Methodologies 26 - 30: FMM LMPs vs Net Load and Average Gas Price

Table 32. Methodology 26: Linear, 97.5, 30/30, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.60%	29.65	28.63	0.64
February 2022	97.16%	36.53	35.70	0.52
March 2022	97.11%	32.73	31.40	0.52
April 2022	96.99%	36.37	32.29	0.57
May 2022	97.80%	50.96	48.59	0.51

June 2022	97.79%	69.91	67.78	0.47

Figure 70. Hourly boxplot of difference, methodology 26: Linear, 97.5, 30/30, 15 min

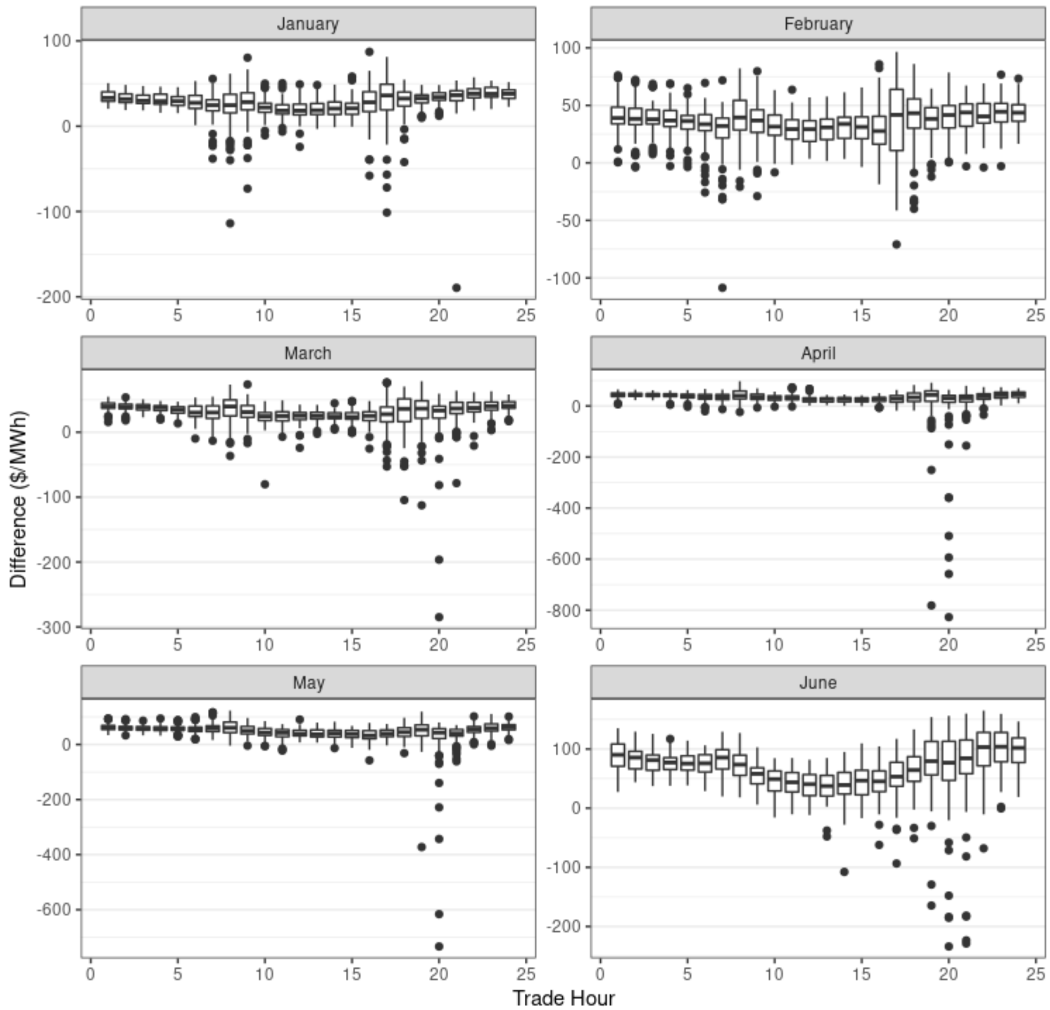


Figure 71. Hourly boxplot of scale, methodology 26: Linear, 97.5, 30/30, 15 min

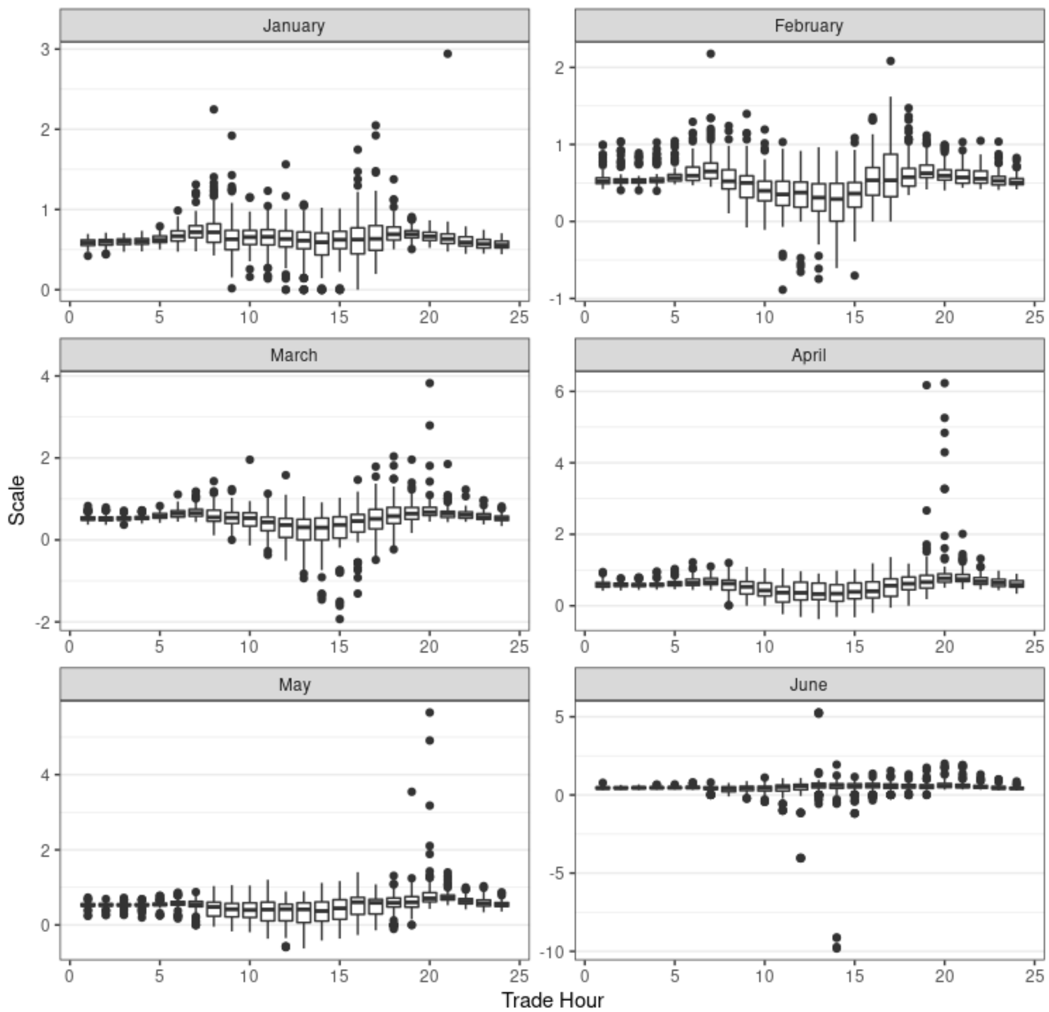


Table 33. Methodology 27: Linear, 97.5, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	98.48%	37.66	36.90	0.57
February 2022	97.09%	35.85	34.96	0.52
March 2022	96.67%	30.29	28.82	0.53
April 2022	96.54%	34.65	30.28	0.59
May 2022	97.97%	52.29	50.08	0.51
June 2022	97.71%	66.63	64.00	0.50

Figure 72. Hourly boxplot of difference, methodology 27: Linear, 97.5, 60/60, 15 min

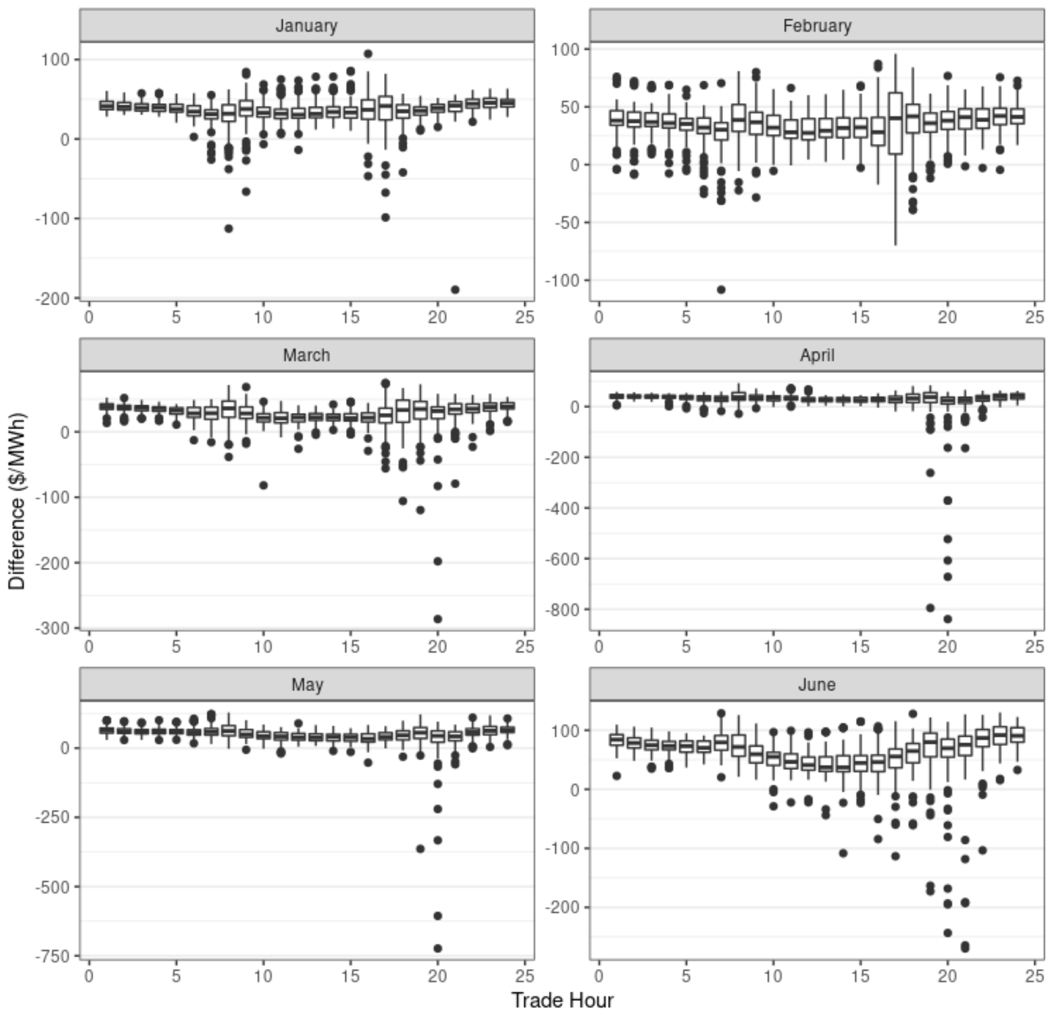


Figure 73. Hourly boxplot of scale, methodology 27: Linear, 97.5, 60/60, 15 min

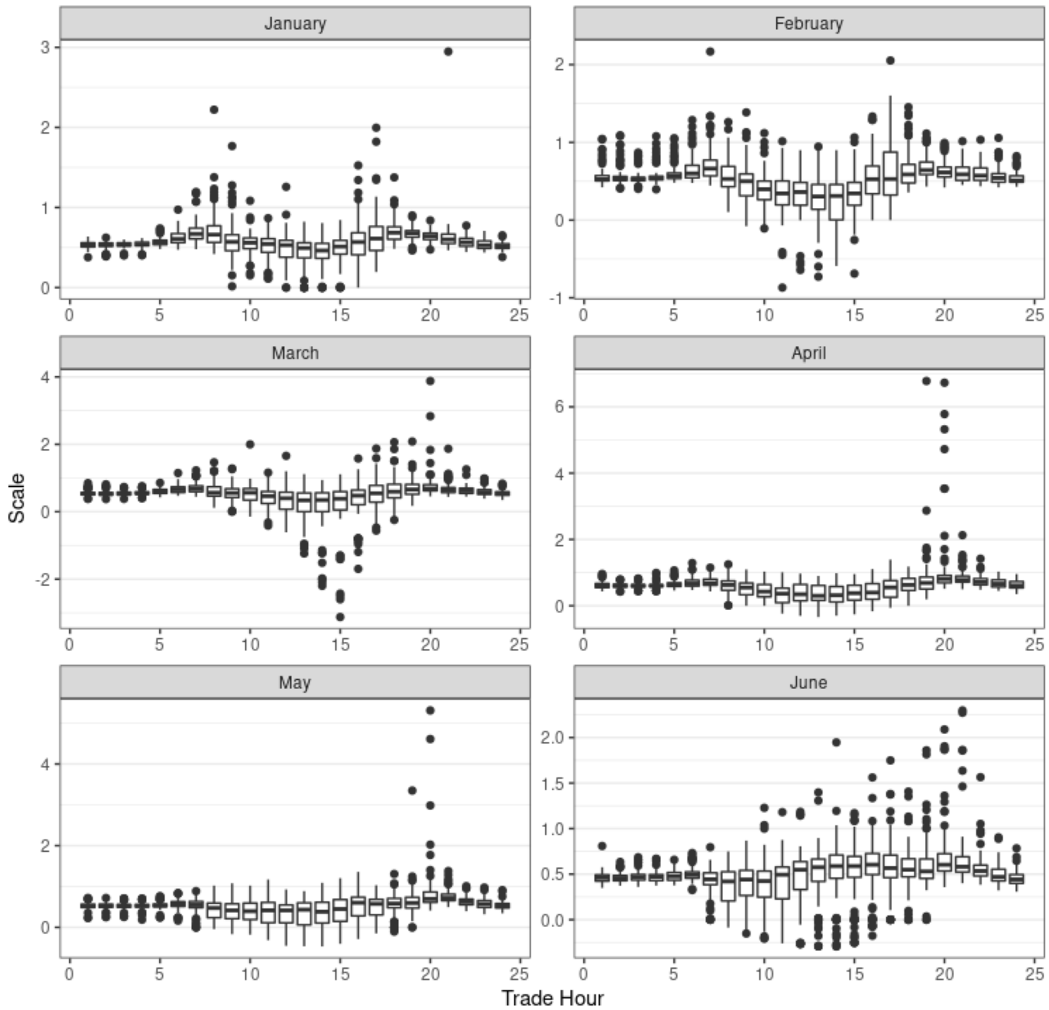


Table 34. Methodology 28: Linear, 90, 60/60, 15 min

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	92.50%	17.62	15.41	0.76
February 2022	90.62%	19.99	17.14	0.67
March 2022	88.28%	17.40	13.75	0.68
April 2022	86.71%	24.03	16.68	0.70
May 2022	94.34%	35.53	31.47	0.61
June 2022	91.98%	36.17	30.03	0.67

July 2022	88.76%	26.33	21.16	0.78
August 2022	91.21%	38.80	21.16	0.81
September 2022	91.66%	86.25	-11.50	0.91

Figure 74. Hourly boxplot of difference, methodology 28: Linear, 90, 60/60, 15 min

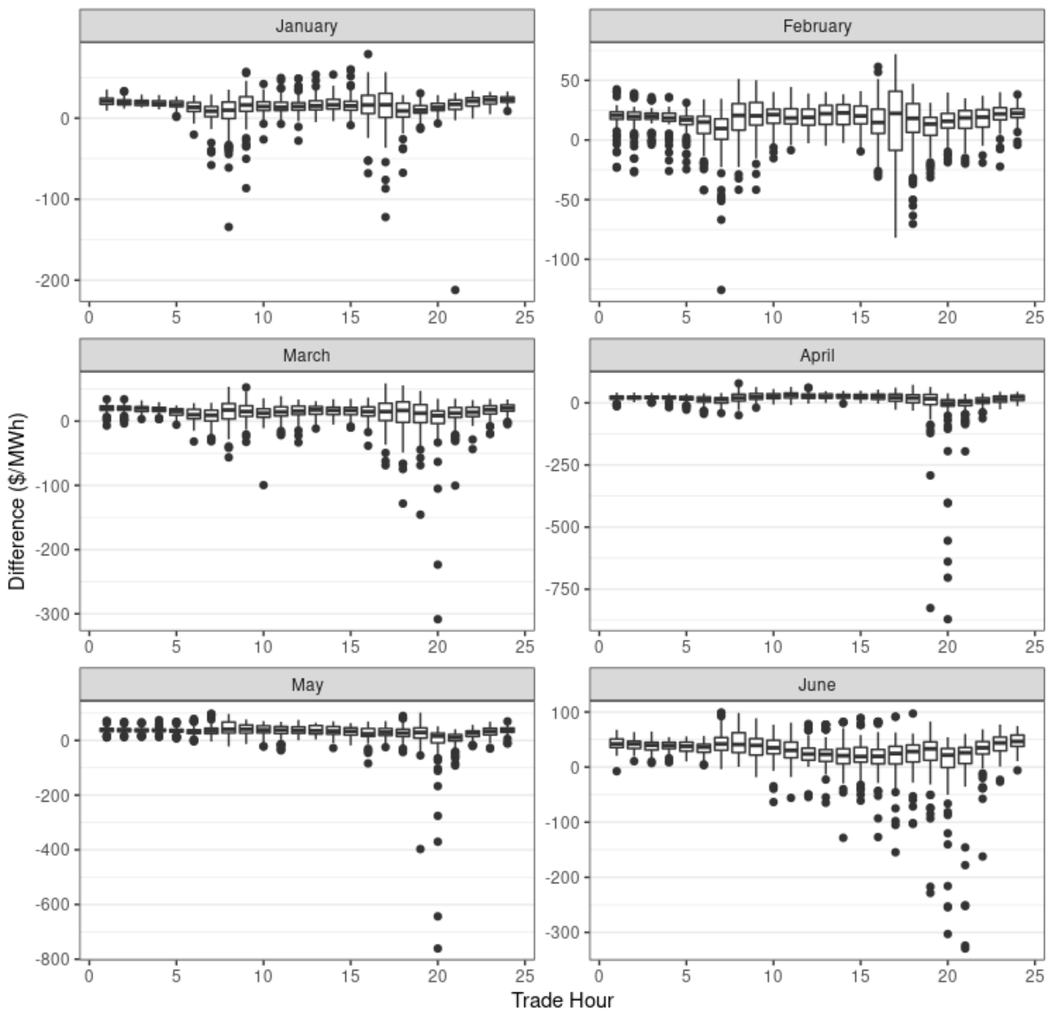


Figure 75. Hourly boxplot of difference, methodology 28: Linear, 90, 60/60, 15 min; summer 2022

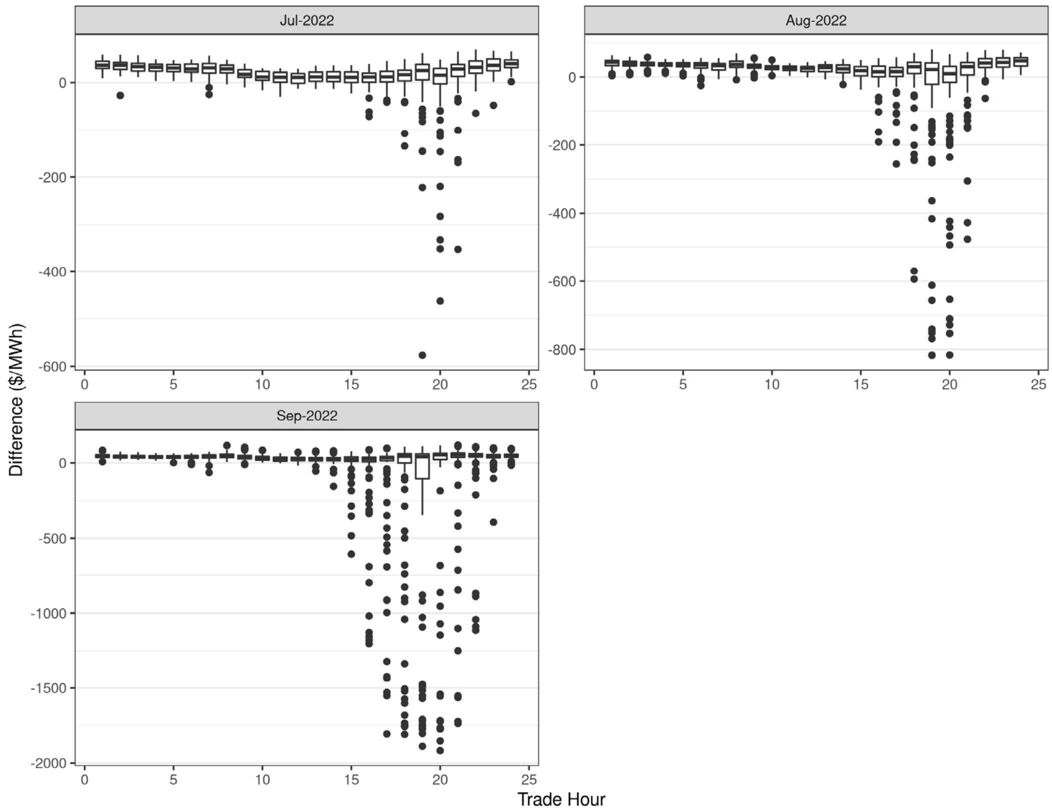


Figure 76. Hourly boxplot of scale, methodology 28: Linear, 90, 60/60, 15 min

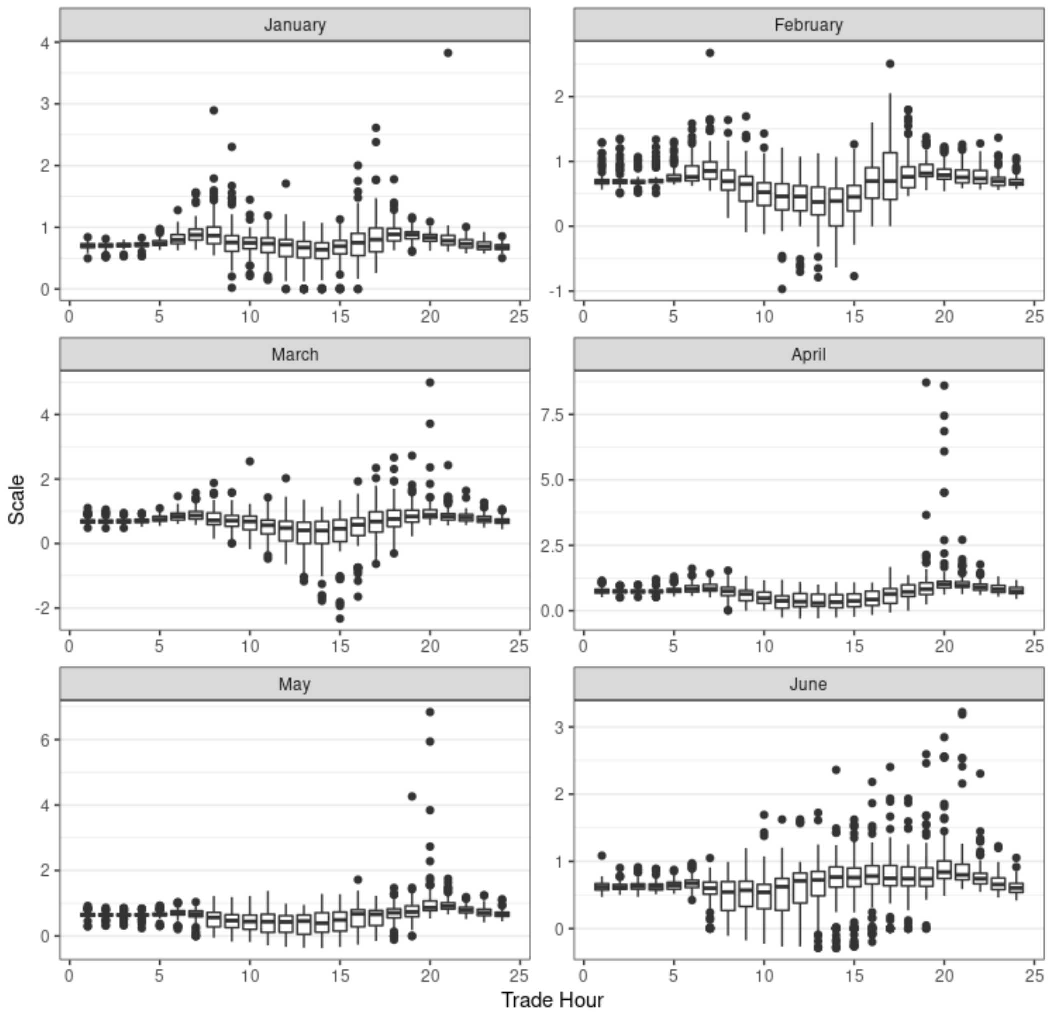


Figure 77. Hourly boxplot of scale, methodology 28: Linear, 90, 60/60, 15 min; summer 2022

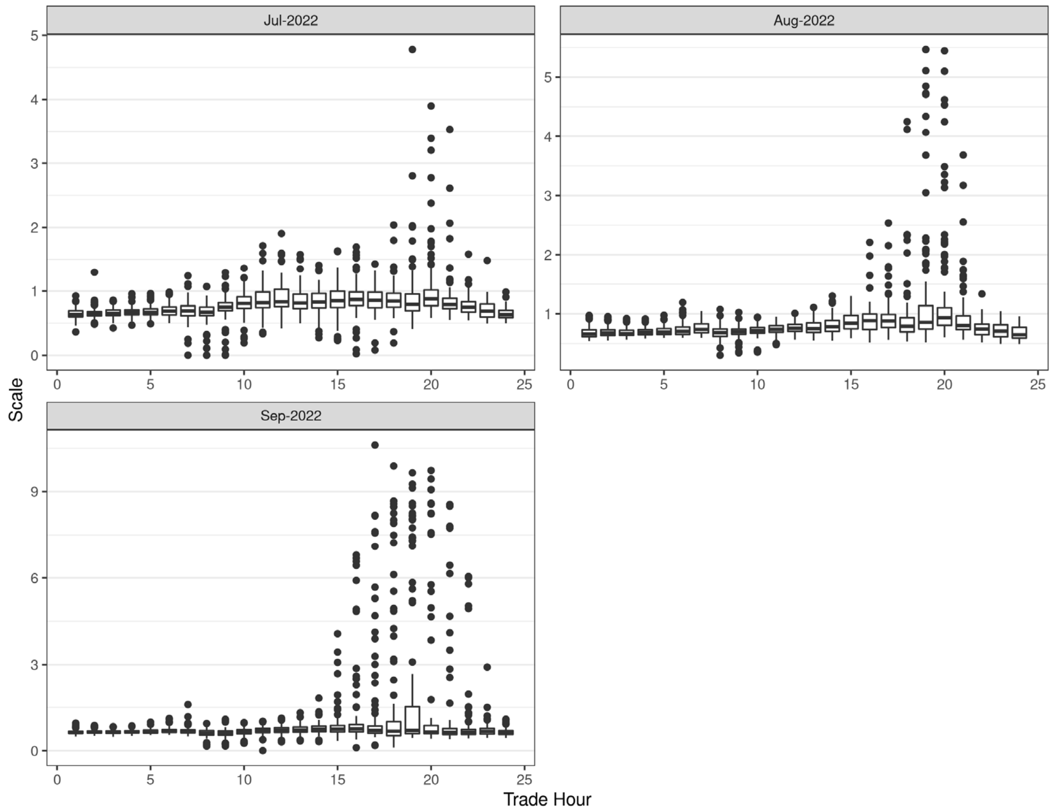


Table 35. Methodology 29: Linear, 90, 60/60, 15 min, 1.2 scalar

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.80%	29.94	28.88	0.63
February 2022	96.34%	30.60	29.42	0.56
March 2022	95.62%	26.80	24.97	0.57
April 2022	96.08%	35.93	31.28	0.58
May 2022	97.83%	52.63	50.21	0.51
June 2022	96.41%	53.92	50.24	0.56
July 2022	96.61%	43.64	40.57	0.65
August 2022	96.56%	60.84	46.58	0.67
September 2022	94.43%	106.27	13.65	0.76

Figure 78. Hourly boxplot of difference, methodology 29: Linear, 90, 60/60, 15 min, 1.2 scalar

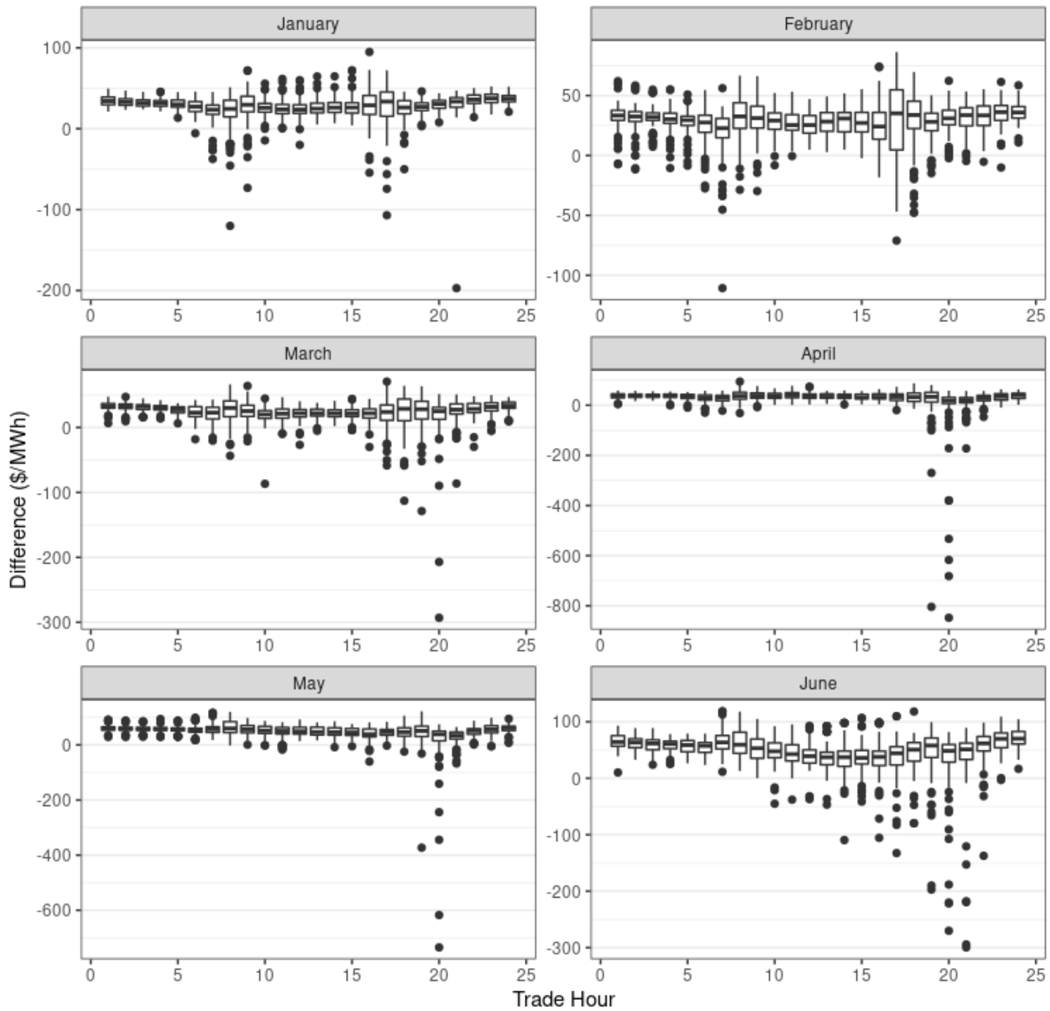


Figure 79. Hourly boxplot of difference, methodology 29: Linear, 90, 60/60, 15 min, 1.2 scalar; summer 2022

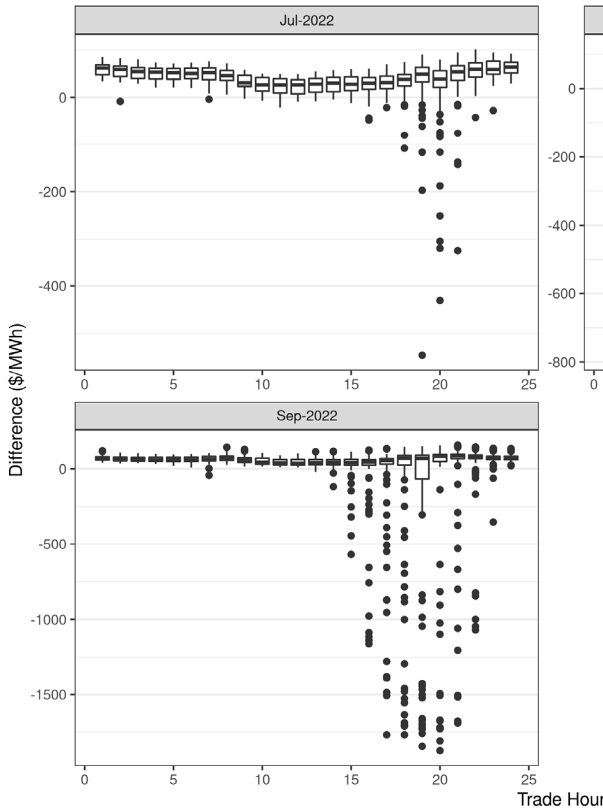


Figure 80. Hourly boxplot of scale, methodology 29: Linear, 90, 60/60, 15 min, 1.2 scalar

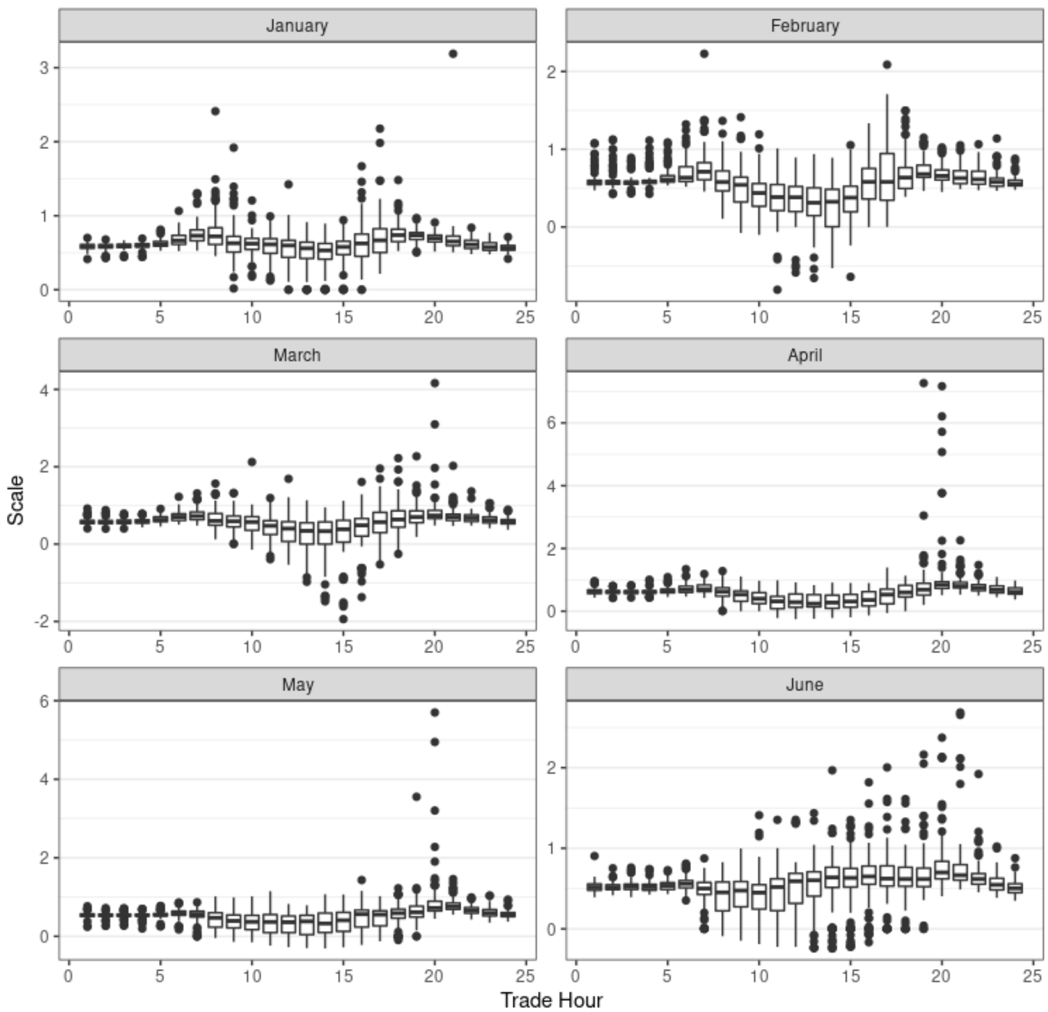


Figure 81. Hourly boxplot of scale, methodology 29: Linear, 90, 60/60, 15 min, 1.2 scalar; summer 2022

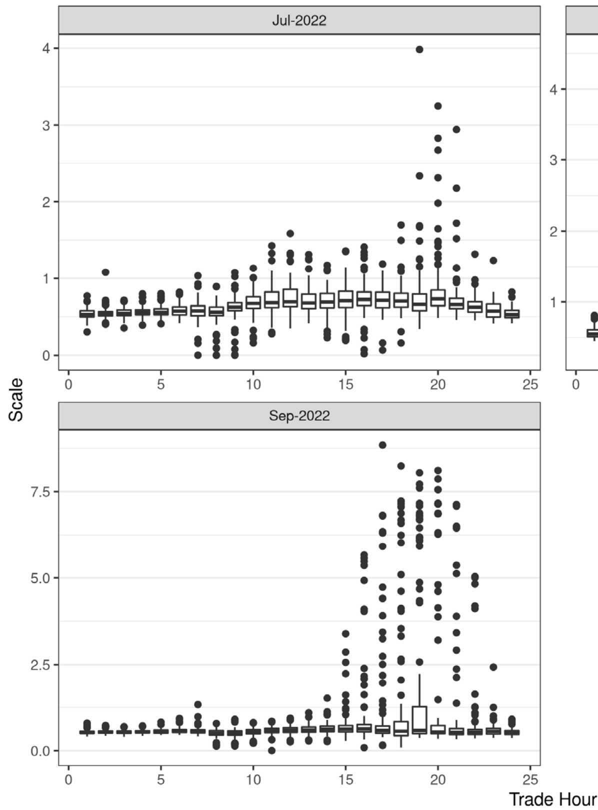


Table 36. Methodology 30: Linear, 90, 60/60, hourly

Month	Percent Coverage	Average Closeness	Average Difference	Average Scale
January 2022	97.80%	30.20	29.11	0.63
February 2022	95.40%	28.94	27.40	0.58
March 2022	94.40%	24.52	22.39	0.59
April 2022	93.99%	29.99	24.84	0.63
May 2022	96.78%	45.49	42.82	0.55
June 2022	97.40%	60.33	57.37	0.52

Figure 82. Hourly boxplot of difference, methodology 30: Linear, 90, 60/60, hourly

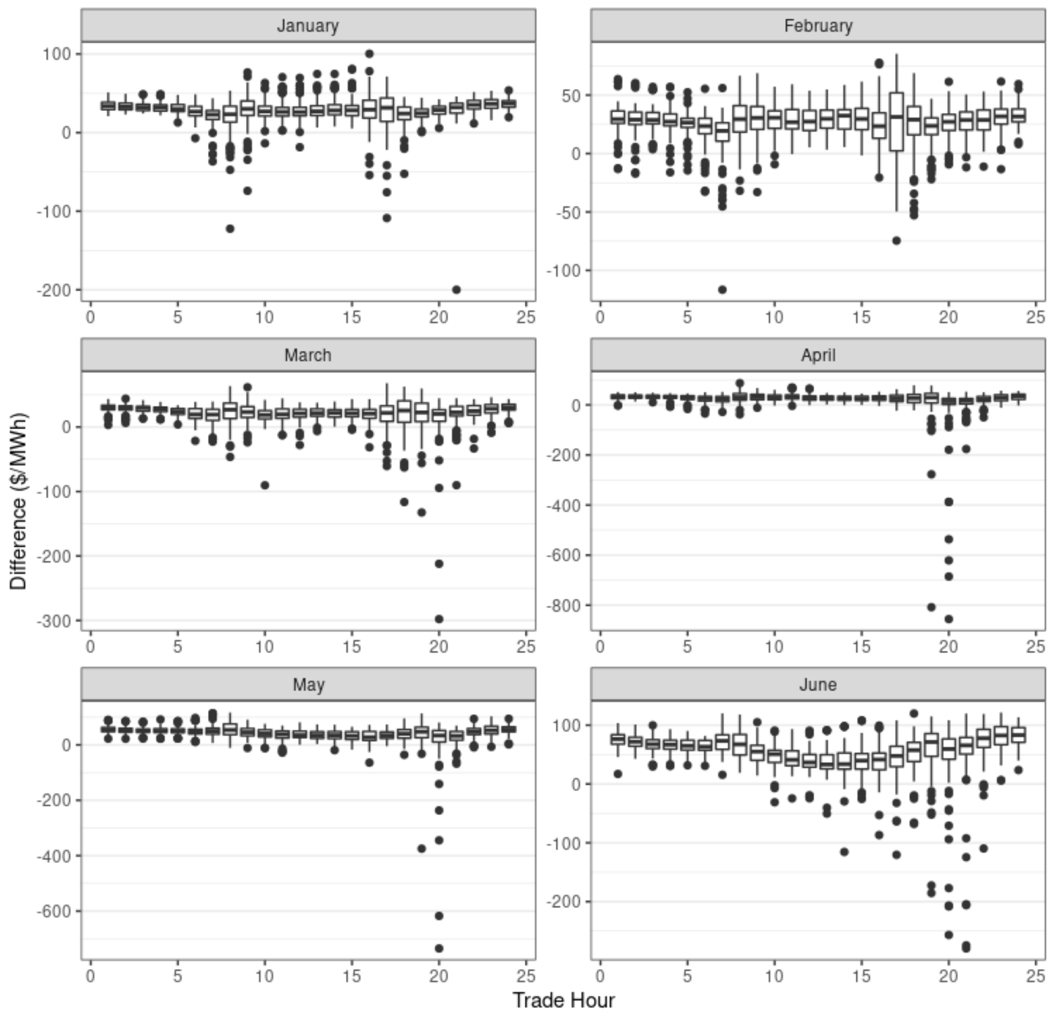


Figure 83. Hourly boxplot of scale, methodology 30: Linear, 90, 60/60, hourly