The Effect of Uncleared Capacity Load Reductions on Peak Forecasts

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CONTENTS

1. INTRODUCTION

This report provides the results of Resource Insight's analysis of the effects of load reductions on a varying number of days per year over a varying number of years. This work arose from discussion among the sponsors of the 2018 Avoided Energy Supply Cost (AESC) study who identified a need for greater clarity on the effect of changes in load on the ISO New England load forecasts and hence on future capacity requirements.[1] This analysis included the construction of a regression model to mimic the ISO New England forecast model and the variation of the historical data to determine the effect of targeted load reductions for the Forward Capacity Auctions (FCAs). We interpret these effects as having an impact on the future value of capacity demand reduction induced price effect (DRIPE).

Our modeled results indicate that a load reduction program that occurs on even a single peak day each summer can affect the load forecast used in the FCA. In most situations, the load forecast will fall more if the historical load is reduced for more days per year or for more years. Regardless of the number of days that a program reduces load annually, the reduction in the load forecast rises steadily for at least eight years. If the program reduces load on less than 55 days, the forecast reduction continues to increase until the program has been running for 12 days. For programs that reduce load on less than 13 days annually, running the program for more years continues to depress the load forecast further, up to the 15 years' worth of historical data that ISO New England uses to develop each load forecast.

1.1. Background

This issue is specific to uncleared load reduction programs or those resources that do not participate in FCAs. These would include load reductions from some behavioral programs and rate-design initiatives that are not eligible capacity resources. Although these uncleared resources do not receive capacity payments, they reduce the aggregate amount of capacity that is required, and hence the price of that capacity, by reducing the ISO New England peak load forecast used in the FCA for that year.

The quantity and price of the capacity obligations acquired in the FCA of a particular year (year t) depend on the forecast prepared in the previous year ($t - 1$). That forecast is built upon a regression analysis constructed from daily historical data from each of the 62 days in July and August for the previous 15 years ($t - 16$ to $t - 2$), which consists of 930 data points. The regression formulation for the forecast (which is used for the Capacity Energy Load and Transmission (CELT) report and the Regional System Plan (RSP) for years t to $t + 9$, as well as the FCA for the year starting in $t + 4$) may vary from year to year, but appears to consistently include multiple independent variables computed from a weighted

[1] See the 2018 AESC Report, Chapter 5. Avoided Capacity Costs (available at http://www.synapse-energy.com/sites/default/files/AESC-2018-17-080-Oct-ReRelease.pdf) for more information. Specifically, see page 105 of the 2018 AESC Report for some discussion of this issue.

temperature-humidity index (WTHI), including an annual time trend times WTHI and the gross energy forecast (before energy-efficiency and behind-the-meter photovoltaic solar).

Our analysis reconstructs a proxy ISO New England load forecast in order to quantify the impact different load reductions over different time periods and under different conditions.

2. THE REFERENCE REGRESSION MODEL

We constructed our proxy for the ISO New England forecast model based on the data used in the 2017 CELT forecast, which was used in FCA 12 to procure capacity for the summer of 2021.[2] All of the effects described below for the reference regression model are for load reductions of various numbers of years that would have been used in producing the 2017 CELT forecast for summer 2021, which was the basis for the demand curve used in FCA 12. A one-year load reduction would affect only the 2016 summer peak day(s), a two-year reduction would affect 2015 and 2016, a three-year reduction would affect 2014–2016, and a 15-year reduction would reduce peaks in 2002–2016.

2.1. Input data

Although we consulted with ISO New England on its forecast data, ISO New England did not provide us with its proprietary demand model data or any details on the functional form of its regression model, beyond those in the Forecast Data summaries provided on the ISO New England web site.[3]

Since we did not have ISO New England's exact data, we needed to develop a proxy dataset. As a result, our analysis should be interpreted as an estimate of load reduction effects, based upon data and using a model similar to that currently used by ISO New England. We do not claim that our model is a precise prediction of future ISO New England forecasts. Since ISO New England's data and its model structure change (at least a little) every year, we cannot anticipate the exact form of the ISO New England load forecast model for any specific future year.

Development of proxy data

We made a number of assumptions to generate our proxy historical dataset, which may not necessarily match ISO New England's past and future sources and methodology.

[2] FCA 12 was conducted in February 2018 and was the most recent FCA conducted at the time of this analysis. This is also consistent with the CELT forecast used in 2018 AESC.

[3] This data includes ISO New England's computation of daily WTHI and reconstitution of load for peak-hour energy-efficiency reductions, demand response and OP #4 measures, and behind-the-meter solar output.

The dependent variable in the regression analysis is the daily gross peak demand, which is the actual daily peak demand[4] plus the effects of behind-the-meter solar PV and energy-efficiency programs (referred to as "passive demand response" or "PDR" by ISO New England) for both peak demand and energy, as well as the effects of Operation Procedure #4 (OP #4) events and load management on peak (which is available only for the summer and winter peaks).[5] Our understanding is that ISO New England uses a proprietary data service to estimate the output of installed solar capacity in each historical hour, while assuming that every hour's PDR reduction is equal to the PDR resource cleared in that capacity delivery year.

We estimated historical daily gross peak load as the sum of (a) the maximum hourly demand for the day in ISO New England's hourly load data files[6] and (b) the summer peak PV and PDR reported in the ISO New England's 2017 Forecast Data spreadsheet for the year.[7] We computed the gross monthly net energy for load (NEL) by multiplying the historical monthly sum of actual load by the ratio of gross annual energy to net annual energy from the ISO New England 2017 Forecast Data.[8]

We computed the ISO New England temperature-humidity index (THI) for each day (0.5 × dry-bulb temperature + 0.3 × wet-bulb temperature + 15) as the weighted average of the THI's from eight weather stations around the region.[9] We then computed the WTHI for each day using ISO New England's formula (weights of 10 for today's THI, 5 for yesterday's THI, and 2 for the previous day).[10]

2.2. Model specification

We estimated the historical relationship of gross load to WTHI, time, NEL and other variables with an ARIMAX (Auto-Regressive Integrated Moving-Average model with eXogenous variables) regression model.[11] This model incorporates both exogenous variables (e.g., net energy for load, weather) and the

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4 Actual daily peak demand is available from the ISO New England website.

5 For more information on OP#4 events, see https://www.iso-ne.com/static-assets/documents/rules_proceds/operating/isone/op4/op4_rto_final.pdf

6 See https://www.iso-ne.com/isoexpress/web/reports/load-and-demand/-/tree/sys-load-eei-fmt for more information.

7 CELT 2017 Forecast Data File, Tab 5, WN. CELT 2017 was analyzed, as it was the projection used as the basis of the 2018 AESC Study.

8 CELT 2017 Forecast Data File, Tab 1, History, Gross ISO-NE Coincident Summer Peak.

9 Weather data were downloaded from https://mesonet.agron.iastate.edu/. The Notes sheet of the annual *SMD Hourly.xlsx* file provide the following weights for the weather stations: Windsor Locks CT (27.7%); Bridgeport CT (7%); Boston MA (20.1%); Burlington VT (4.6%); Concord NH (5.8%); Worcester MA (21.4%); Providence RI (4.9%); Portland ME (8.5%). We used the same weights for all years; we have not been able to confirm whether ISO New England has changed the weights over time, as load (especially summer peak) has increased in northern New England compared to the southern portion of the region.

10 Forecast Modeling Procedure for the 2018 CELT, May 1, 2018, page 9. https://www.iso-ne.com/static-assets/documents/2018/04/modeling_procedure_2018fcst.pdf. Note that this document contains all citations for coefficients and weights used in this analysis.

11 See www.statsmodels.org/devel/generated/statsmodels.tsa.statespace.sarimax.SARIMAX.html for more information.

autoregressive error terms that ISO New England uses in its regression model. These are summarized in Table 1.

Table 1. Variables used in summer peak model

Variable	Definition
Intercept	Constant Term
PEAK	Daily Peak Load, MW
MA_NEL	12-month Moving Sum Annual Net Energy for Load, GWh
WTHI_SQ	The square of [the 3-day Weighted Temperature-Humidity Index at Peak– 55°]
TIME_WTHI	Year indicator; (2002=11, …, 2016=25) × WTHI
Weekend_WTHI	WTHI for a weekend day, else 0
July_04WTHI	WTHI for July_4, else 0
HOLWTHI	WTHI for a Holiday, else 0
Yr2005	1 if Year=2005; 0 otherwise
Yr2012	1 if Year=2012; 0 otherwise
AR(1)	Correction for autocorrelated error from the previous year
AR(2)	Correction for autocorrelated error from the two years previously

The independent variables included the following for each July and August day in 2002 through 2016:

- Net Energy for Load, grossed up for PV and EE, over the twelve months ending in the current month (July or August, depending on the data point), as described in the previous section.
- The 3-day weighted temperature-humidity index (WTHI) for the eight cities used in ISO New England's own modeling of weather (see footnote 5). In our analysis, following the treatment in the ISO New England model, the WTHI variable is used as the square ($[\text{WTHI}–55]^2$), and as various cross terms, such as WTHI × weekend dummies.
- Year × (WTHI–55), where the year index is the calendar year minus 1991.
- Boolean flags (i.e., dummies) for holidays, July 4th, weekends, the years 2005 and 2012, and WTHI times the dummy variables for weekends, holidays and July 4th.[12]

Table 1 reproduces the description of the summer peak model in the Peak Definitions in ISO New England's 2017 Regional and State Energy & Peak Model Details, corrected to reflect conversations with

[12] It is unclear why ISO New England included variables for both holidays and July 4th, since the only holiday in the two summer months is July 4th. We used the two redundant variables; collectively, the two dummies should capture the effect of July 4th. It is also not unclear why the years 2005 and 2012 featured Boolean flags.

the ISO forecasters and the specific model described in the Summer Peak Models tab of the Model Details.[13]

2.3. Forecast data

Once we developed the regression equation, we required forecast input values for the equation. ISO New England provides the forecast gross energy for load in its forecast.[14] Projection of the time trend and binary variables is straightforward: 2017 is year 26, 2018 is year 27, etc.; the weekend binary equals WTHI on future Saturdays and Sundays, the July 4 and holiday binaries equal WTHI on July 4 each year.

ISO New England's forecasting method does not use a single WTHI value, but instead identifies the highest load for a variety of input conditions:

> Weekly peak load forecast distributions are developed by combining output from the daily peak load models with energy forecasts and weekly distributions of weather variables over 40 years.
>
> The expected weather associated with the seasonal peak is considered to be the 50th percentile of the top 10% of the pertinent week's historical weather distribution. The monthly peak load is expected to occur at the weather associated with the 20th percentile of the top 10% of the pertinent week's weather distribution. The "pertinent week" is the week of the month or season with the most extreme weather distribution. For resource adequacy purposes, peak load distributions are developed for each week of the forecast horizon.[15]

We do not have access to the distributions that ISO New England used in this method, nor do we have a clear operational description of the method. Therefore, we performed a calculation to estimate a value of WTHI that best reproduced the 2017 CELT peak forecast, which turned out be 81.4°.

2.4. Base forecast benchmarking

Figure 1 summarizes our modeled Gross and NET 2017 forecast against the 2017 reported Gross and NET CELT forecast. Our modeled forecasted peak demands closely match the ISO's 2017 CELT forecast. Our forecasts for gross peak are within 0.2 percent of the 2017 CELT forecast for 2021, the year for which the 2017 forecast determined the installed capacity requirement.

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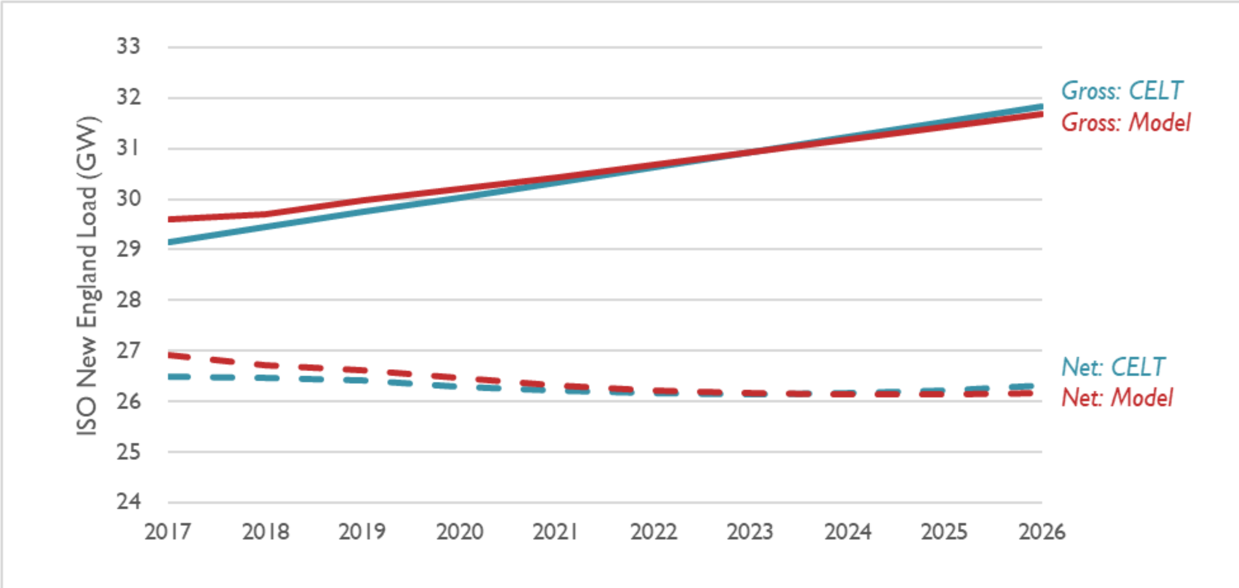
[13] The ISO New England forecast documentation sometimes refers to gross loads as net of PV and PDR, and the Forecast Modeling Procedure for 2017 CELT describes the composite time variable as using WTHI–55º, while the 2017 Regional and State Energy & Peak Model Details file suggests that WTHI is not reduced by 55º.

[14] 2017 Forecast Data File, Tab 6, Monthly NEL.

[15] Forecast Modeling Procedure for the 2018 CELT, May 1, 2018, p. 6.

Figure 1. Comparison of forecasts of gross and net Summer Peak, 2017 CELT and Resource Insight modeled proxy



3. THE EFFECT OF LOAD REDUCTIONS ON THE FORECAST

3.1. Structure of reductions

Using our constructed base forecast, we estimated how various load reductions in 2002 through 2016 would have affected the ISO New England load forecast for 2021. Each sensitivity run for the analysis consisted of four steps:

1. Reduce historical gross peak demands on a specified number of summer event days (*d*) for a specified number of years (*y*) by a constant number of megawatts (MW) (ΔL).
2. Estimate new regression model coefficients using the same functional form and the modified historical data.
3. Develop peak demand forecasts for the years 2017–2026 (and most importantly, 2021) using the new coefficients.
4. Compute the ratio (*R)* of the change between forecast peak (ΔF) to the load reduction (ΔL).

The ratio *R* can be thought of as a measure of the efficiency of load reduction in reducing the forecast.

For ΔL, we tested load reductions of 250 MW, 500 MW, and 1,000 MW. We used the same reduction in all the days and all the years adjusted in any particular run.

For *d*, we reduced load on the highest days, from one event day to all 62 summer days per affected year. We tested reductions on the highest-load days and the highest-WTHI days and looked at the effect of imperfect forecasting of peak days.

For *y*, we reduced load on the most recent years, from just one year (2016) to all 15 years 2002–2016.

3.2. The effect of lower input values on regression forecasts

When we undertook this analysis, we expected that reductions on more days, and reductions in more years, would consistently push down the forecast further. As we discuss in the next section, that is not what we found. Before presenting our results, we will explain how they can arise.

The next four figures show a regression through 15 years of base data, which in this case we have set to 1.5 percent annual growth as a hypothetical.[16] In each figure, we show the base historical data, the linear trend line with the base data (which produces a forecast of 32,320 MW in 2021), the historical data that would have been observed with 1,000 MW reductions in some years, and the regression trend line with the modified data. Figure 2 shows the effect of load reductions in the last two years of data,

[16] A comparable analysis using weather-normalized loads before PDR and PV for 2002 through 2016 produced very similar results, but is a little harder to read, due to the drop in load associated with the Great Recession in 2009 and 2010.

representing a demand response program operating in 2015 and 2016. The trend line tilts so that the trend is higher than the actual load in the first few years and in the last two years (the ones with demand response reductions), but lower than the input data for 2008–2014. The projection for 2021 is about 700 MW lower than in the base case.

Figure 2. Effect of two years of demand response on the forecast

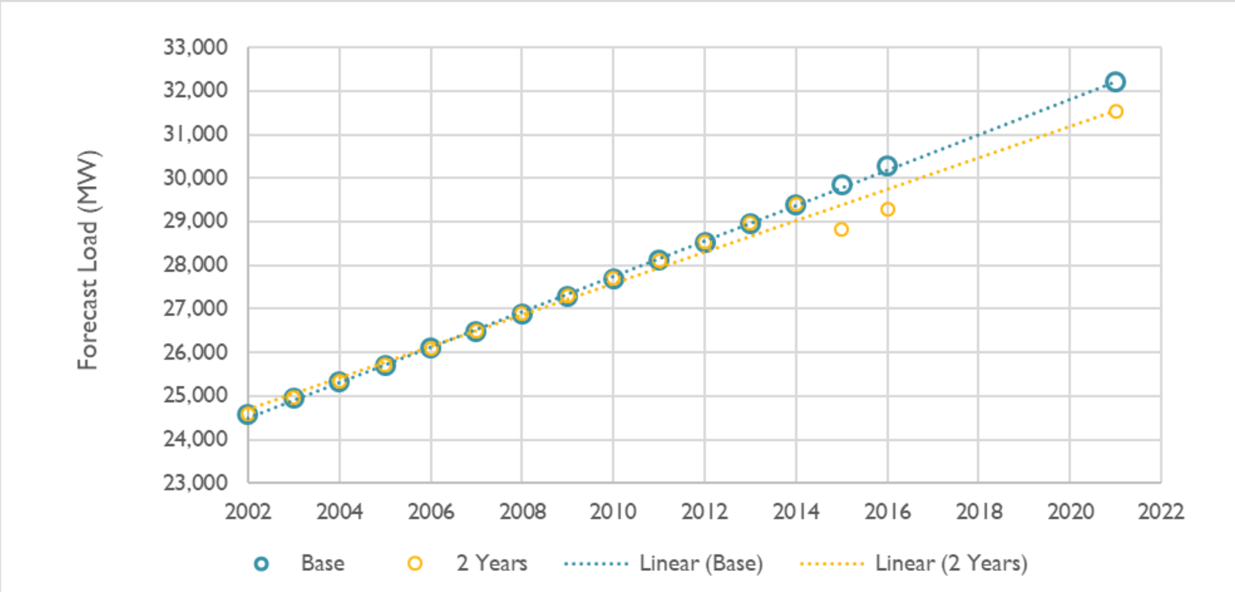


Figure 3 shows the effect of five years of demand response reductions. The trend line with the demand response has tilted further, so that it is almost 1,000 MW below the base-case trend by 2016, and 1,400 MW below the base-case forecast for 2021. The trend line mostly rotates clockwise, rather than moving down, so the change from the base case increases over time and the reduction in the 2021 forecast is substantially larger than the reduction in loads in the five years affected by demand response.

Figure 3. Effect of five years of demand response on the forecast

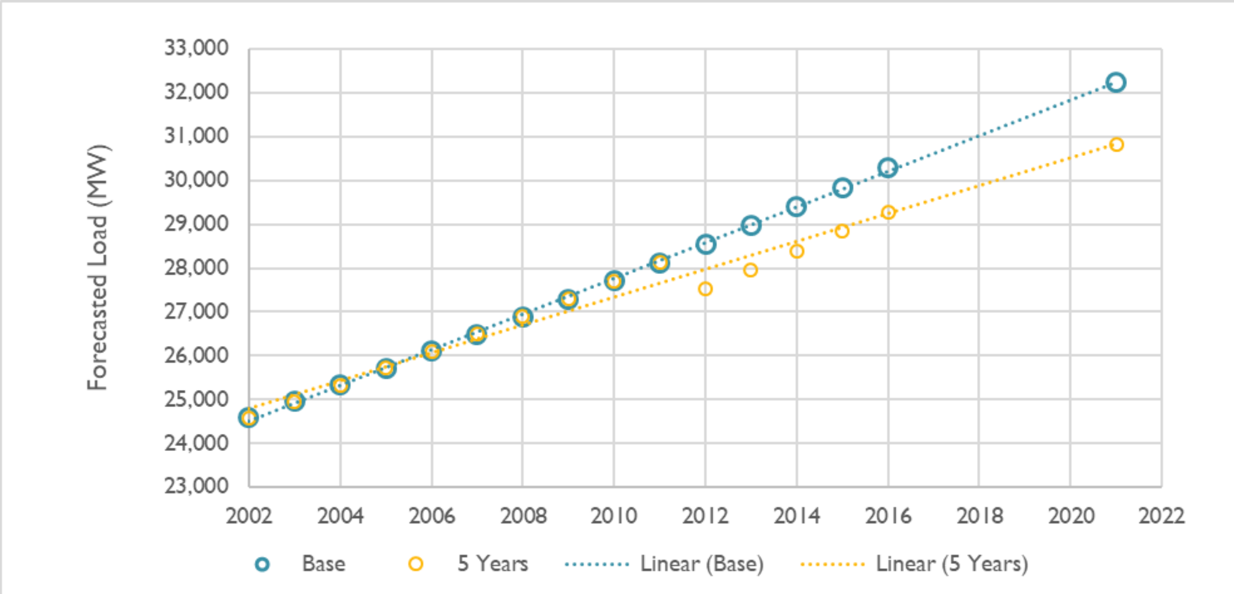
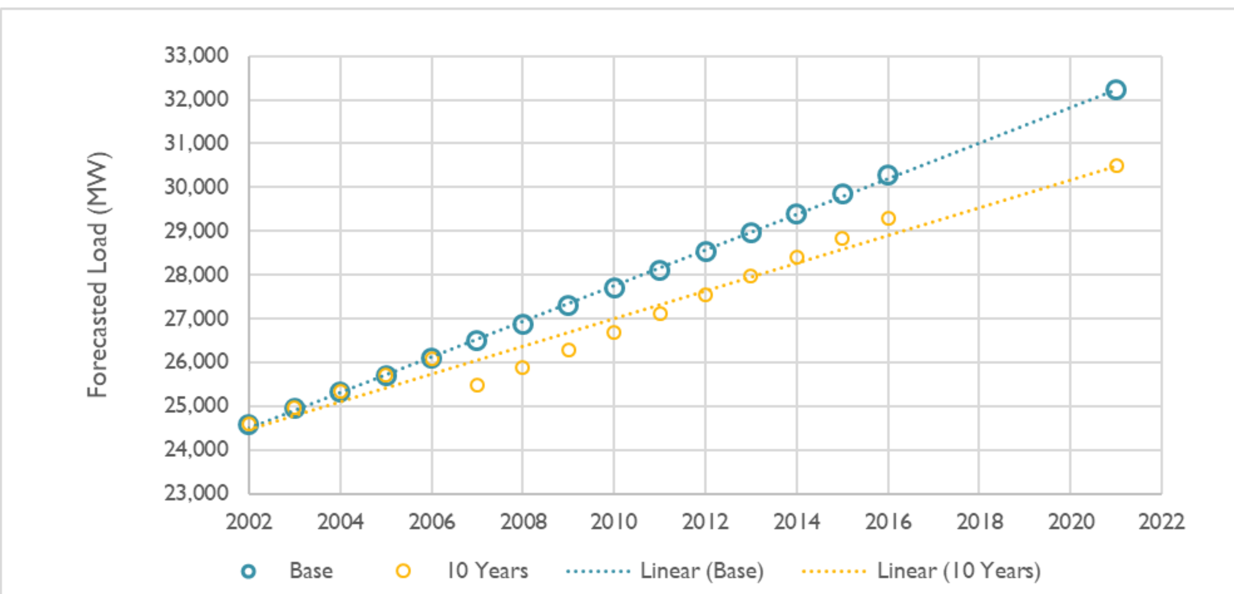


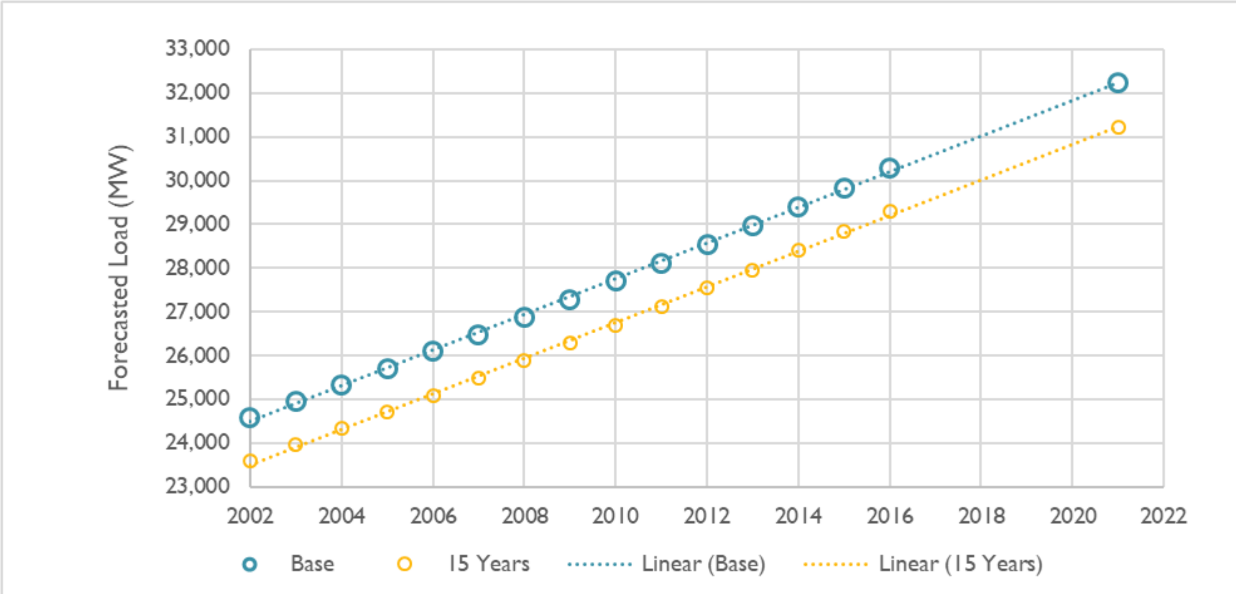
Figure 4 shows the effects of nine years of demand response, which continues the pattern in Figure 3; the forecast for 2021 would be almost 1,800 MW below the base case.

Figure 4. Effect of nine years of demand response on the forecast



Finally, Figure 5 shows that 15 years of 1,000-MW load reductions lowers the trend line by 1,000 MW, while leaving the slope the same as in the base case. The forecast for 2021 is thus 1,000 MW lower than in the base case.

Figure 5. Effect of 15 years of demand response on the forecast



Thus, demand response in some number of the latest years will tend to produce forecast reductions that exceed the annual reductions in the historical data. Beyond some point, additional years of demand response will result in smaller forecast reductions, and once the demand response effect has been in effect for the entire study period, the forecast reduction will equal the reduction in the annual input data.

The same pattern would be expected as the reductions are extended to more of the highest-load days in each year.

3.3. Results for reductions on highest-load days

Not surprisingly, we found that the decreases in the forecast peaks based on load reductions varied with (a) the number of days on which load was reduced each year and (b) the number of years of load reductions in the historical load data. Interestingly, we found that the size of the load reduction had essentially no effect on the ratio *R*. If load is reduced 100 MW on the five highest-load days in each of the last five summers in the modeling dataset (2012–2016), the forecast for 2021 would be reduced by 24 MW; if the reductions in the historical load were 1,000 MW, the forecast would be reduced by 240 MW.

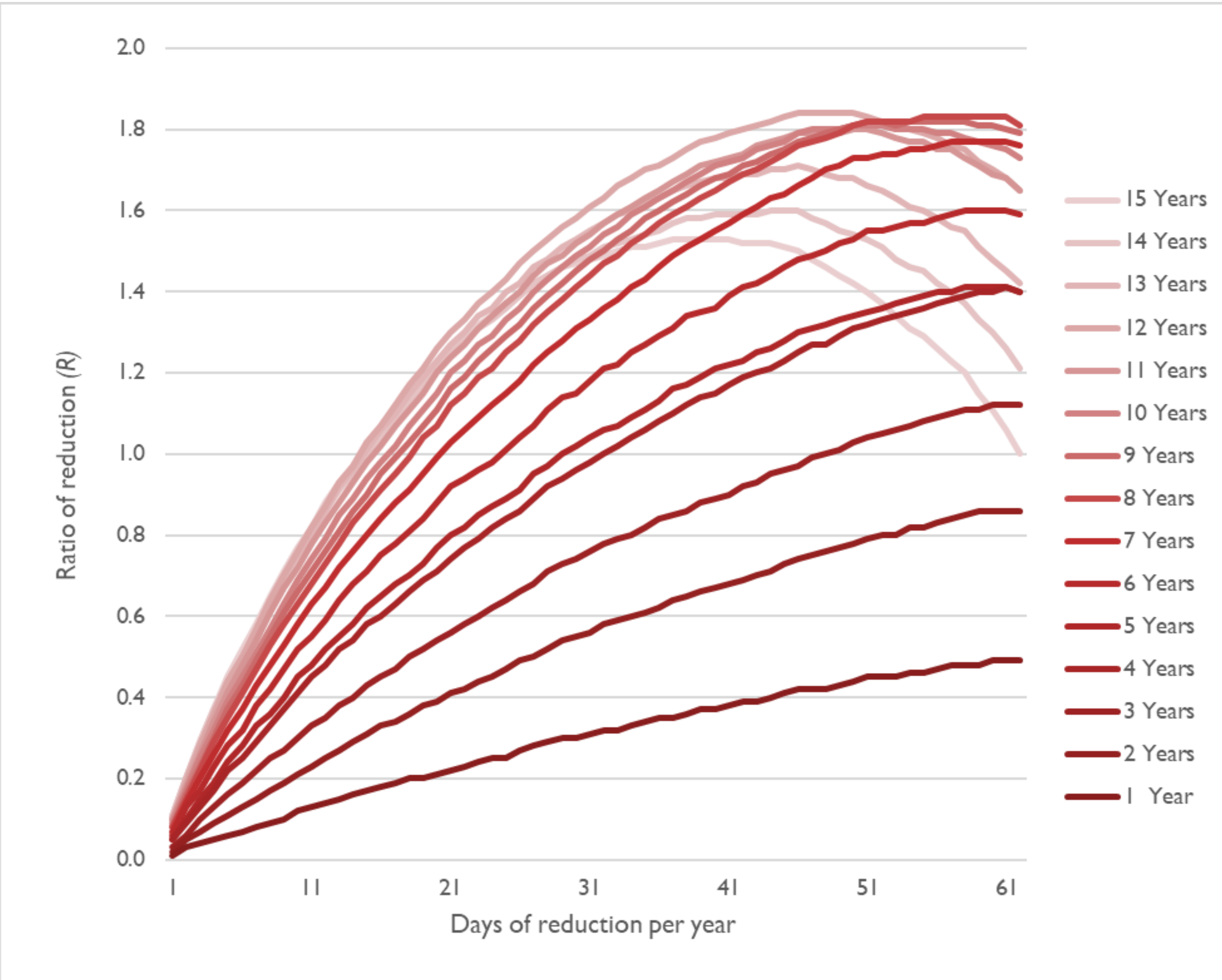
For any duration of a load reduction program, the value of *R* rises with the number of days in which load is reduced, up to at least 35 days. For load reduction programs lasting more than eight years, the value of *R* begins to fall if the number of days reduced exceeds some threshold; at about 55 days for a 9-year program and at about 40 days for a 15-year program.

However, the value of *R* did not vary monotonically with respect to either the number of days or the number of years, and *R* could be more than 1.0, as shown in Figure 6.

For a load reduction program lasting more than two years, reducing load on a large number of days results in *R* > 1, such that the reduction in the load forecast is larger than the reported reduction in the historical load. For a three-year program, *R* peaks at about 1.1 with reductions in 60 days; programs lasting 8 to 12 years have peak *R* above 1.8 for about 50 days of reductions; and a program that reduces load in all 15 years used in the forecast would have a value of *R* over 1.5 for 31 to 46 days of reduction, with *R* falling rapidly for any additional days.

A program that reduces load for all 62 summer days each year for 15 years has an *R* value of exactly 1.0. In effect, such a program would look, for peak-forecasting purposes, like a cleared energy efficiency measure.

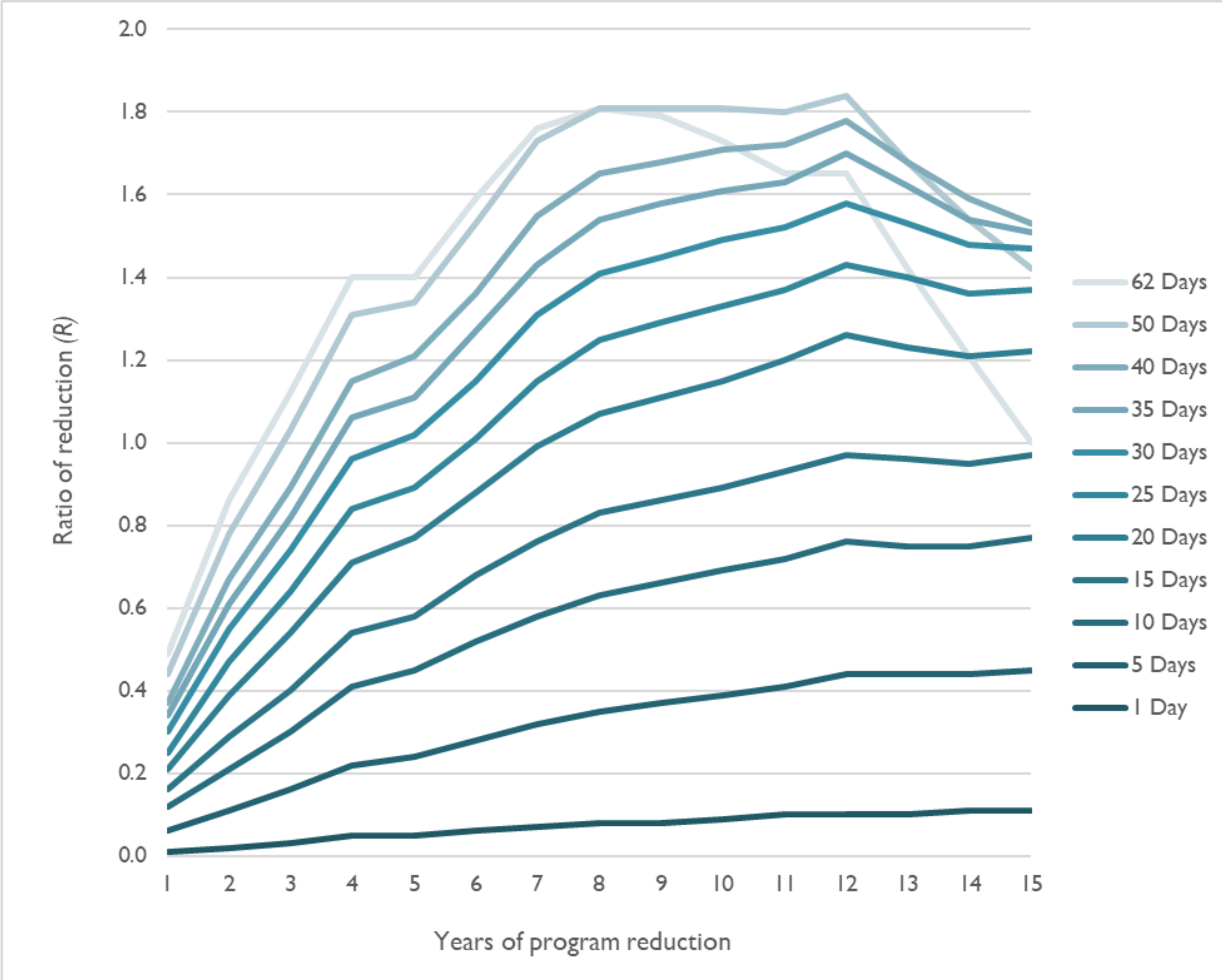
Figure 6. Ratio of forecasted load reduction to historical load reduction, various durations



Note: Ratios are shown for 2021 forecasted year.

Figure 7 provides the same data, but with the duration of the reduction in years on the *x* axis and each line representing a number of days of load reduction in each year (essentially swapping the *x* axis and legend in Figure 6). For purposes of readability, we present only a subset of days, rather than the full 62.

Figure 7. Ratio of forecast reduction to load reduction, various numbers of peak days per year



The horizontal axis in Figure 7 is the number of years that a load reduction has been in place, as of the last year of historical data for the forecast (year *t* – 2). See Appendix A for the *R* values from Figure 6 and Figure 7 numerically.

3.4. Applying the results to demand response screening and valuation

The results in Figure 6 and Figure 7, as well as Appendix A, can be used in at least two ways. First, they can be used to screen potential demand response programs by modifying the value used for capacity DRIPE. For example, a new program that would first reduce load in 2020, for the top ten summer days, would be a one-year reduction in the data for the 2021 forecast, which would be used in the 2022 FCA 16 for the summer of 2025. Since Appendix A shows that a 10-day program has an R value of 0.12, a 200 MW load reduction in 2021 would reduce the forecast peak by 24 MW and produce the DRIPE benefits of that size load reduction.

Once the program has run for three years (2020–2022), it would be a three-year reduction for the 2023 forecast used in 2024 for FCA 18 for the summer of 2027. The program would have an R value of 0.30, so the FCA forecast for 2027 would be reduced by 60 MW. Similarly, if the program continues to run for 15 years, the reduction in the forecast used for FCA 30 would be 154 MW.

Second, the results can be used retrospectively, to evaluate the effect of a program that has been operating. In 2019, a Program Administrator might file results for a 100 MW program that it ran in 2014–2018, reducing load on the top 15 days of each summer. From Appendix A, we would use the 15-day row of Appendix A and estimate that the program reduced the load used in the FCA forecasts by 17 MW in 2018 (for which 2014 was the last year of data used in the forecast), 31 MW in 2019, 43 MW in 2020, and 58 MW in 2021. The sum of the avoided capacity and DRIPE from those years would be benefits of the program.

3.5. Demand response dispatch scenarios

This section describes the results of our analysis under a variety of dispatch and implementation sensitivities, including situations in which demand response is dispatched according to weather or in line with day-ahead forecasts. We also examine situations in which the dispatch of demand response misses some peak days, is performed according to some forecast of load distribution, and in which demand response is dispatched for only a single day each year.

Dispatching according to weather, rather than load

The results above assume that a demand response program identifies the highest-load days and achieves load reduction on those days. The results are essentially identical for a program that concentrates on reducing load on the days with the worst weather (the highest WTHI values), even though those are slightly different from the highest load days.

Dispatching demand response with day-ahead forecasts

The results are also very similar (although the curves are less smooth) if targeting of the demand response is imperfect, such that the program is activated on some days that are not in the *d* highest days. For example, the program administrator may call an event on a day that looks like it will be one of the top *d* days for the summer, but it may turn out to have an actual load lower than expected. Or, it may turn out that there are more higher-load days that occur later in that summer, after the program administrator has called as many days as is allowed by the tariff or contracts.[17]

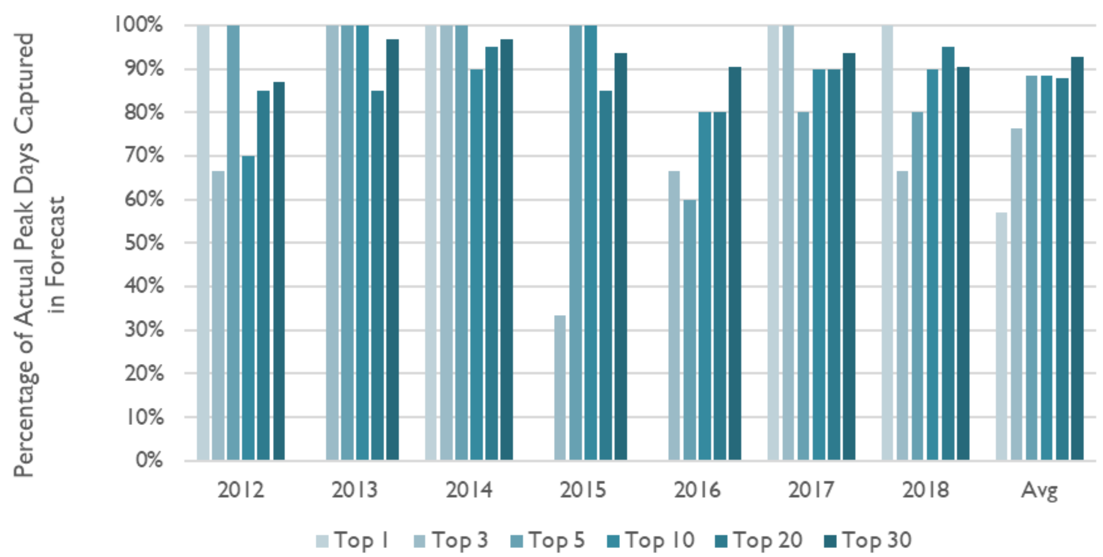
Figure 8 shows the accuracy of demand response program dispatch that is called when the day-ahead peak load is expected to be one of the highest *d* days. These results factor in the optimistic assumption that the program administrator has perfect information about the highest loads for the current summer

[17] The ISO New England day-ahead forecasts are actually quite accurate, correctly flagging the highest *d* days of the summer, if the load of the lowest of those days is known.

but not when those highest load days will occur. With this assumption, programs allowing for 5 to 20 days of load reductions would catch 90 percent of the intended control days.

Where the day-ahead load would result in activation of a day outside the targeted group, it is almost always close to the intended group. For example, a program targeted at the top 10 days might miss day six, but that unused activation would likely be present on day 11 or 12.

Figure 8. Percentage of highest days flagged by day-ahead load forecast, by year



Dispatching demand response, missing some days

Figure 8 shows the targeting errors if the program administrator somehow knew what the load would be on day d, the lowest load day for which the administrator should activate the program. A more realistic simulation would recognize that the program administrator does not know in early July whether the rest of the summer will be hot or mild, and thus will not know whether a particular day-ahead load forecast is likely to be one the *d* highest days.

Table 2 shows how close the load reductions would be to the perfect-information case with typical substitution of peak days with days just outside the targeted period. For example, Sensitivity Case 4 tests the effect on load reductions of calling an event on the 14th highest day rather than the 9th day of a 10-day per year program, while Sensitivity Case 5 models the effect of calling an event on the 14th highest day rather than the 6th day. Other than Sensitivity Case 1 (an unlikely single-day program calling an event on the second-highest day, rather than the highest-load day), the effect of the imperfect dispatch is within 6 percent of the effect of perfect dispatch, and sometimes the dispatch error actually increases the reduction in forecast load.

Table 2. Ratios of forecast reduction with minor dispatch errors, as a percentage of forecast reduction from perfect dispatch

Sensitivity Case	Event Days	Changes from Optimal Dispatch		Years of Operation			
		Top Days Missed	*Non-Top Days added*	*1*	*5*	*10*	*15*
1	1	#1	#2	67%	92%	92%	81%
2	3	#3	#4	99%	105%	99%	98%
3	5	#5	#7	101%	101%	98%	98%
4	10	#9	#14	99%	97%	98%	98%
5	10	#6	#14	99%	96%	98%	97%
6	20	#14, #17	#25, #30	100%	99%	98%	96%
7	20	#11, #12	#22, #23	98%	97%	97%	96%
8	20	#16, #20	#27, #32	103%	100%	98%	97%
9	31	#18, #24, #27, #30	#34, #37, #40, #43	96%	96%	96%	94%
10	31	#18, #27, #31	#34, #37, #40	98%	97%	97%	95%

Table 3 shows the results for poorly targeted dispatch of a load reduction program in the top 30 days of the summer, either 10 events per year on every third day (starting with day 1 or day 2) or 15 events per year on every second day (either the even-numbered days or the odd-numbered). These dispatch choices represent nearly the worst cases for 10 or 15 annual events, yet they still produce 62 percent to 92 percent of the forecast reduction due to load reductions perfectly targeted to the 10 or 15 days with highest loads.

Table 3. Ratios of forecast reduction with even more imperfect dispatch, as a percentage of forecasted reduction from perfect dispatch

Event Days	Dispatch Days, Ranked by Load	Years of Operation			
		1	*5*	*10*	*15*
10	Every 3rd day: 1, 4, 7, 10, 13, 16, 19, 22, 25, 28	85%	78%	75%	68%
10	Every 3rd day: 2, 5, 8, 11, 14, 17, 20, 23, 26, 29	73%	72%	71%	62%
15	Odd days: 1,3, 5, 7, 9, 11,13,15,17,19,21, 23,25, 27, 29	92%	84%	82%	76%
15	Even days: 2, 4, 6, 8, 10,12,14, 16, 18, 20, 22, 24, 26, 28, 30	84%	78%	76%	68%

Dispatching demand response with forecast load distribution

To examine dispatch errors more systematically, we tested a case in which the program was activated and load was curtailed when the day-ahead forecast was within *k*% of ISO New England's forecast of the summer peak, where *k* is the percentage of peak that, on average over the historical data, was exceeded for *d* days per year.

This is a simplified example of a typical demand response program (such as dynamic peak pricing), in which the program administrator tries to foresee peak days and curtail load on those days. In some low-load years, the program will miss some days that later turn out to have been in the top *d* days, while in other years, the program will operate on days that turn out not to be in the top *d* days.

Demand response program administrators are likely to be more sophisticated than the simple algorithm that we used. For example, the program administrator will know how much of the summer remains, how many event days are left for the year, whether the remainder of the summer is forecast to be warmer or cooler than usual, and what a more detailed forecast for the next week or more shows.

Assuming that the program administrator has no information about the loads for the particular year, dispatching with this simple algorithm results in forecast load savings of 80 percent to 100 percent of the perfect-information dispatch, from about four to fifty event days annually. The detailed pattern of differences between the values shown in Appendix A and the values shown in Appendix B may well be due to the different performance of the algorithm in the specific historical years. Overall, a reasonably thoughtful program administrator should be able to achieve about 95 percent of the benefits shown in Appendix A.

Daily dispatch values

Finally, we estimated the effects of load reductions in just a single day each year, from the highest-load day to the lowest-load day of the summer, and for one to fifteen years of program operation. The specific effect of reductions in any particular day is probably very sensitive to the specific historical pattern of daily loads and weather, so the detailed differences in the daily values (for example, between the 18^{th} and 19^{th} days, or between seven years and eight years) may not be significant. See Appendix C for our estimate of the R value (reduction in the 2021 forecast as a fraction of the annual historical load reductions), for various number of years and various numbers of days per year.

These daily values, if summed up for the top *d* days, produce load reductions lower than those we found for reductions in the top *d* days. This is illustrated in Figure 9, Figure 10, and Figure 11, for programs lasting 1, 5, and 15 years, respectively. In each figure, we plot the sum of the daily contributions to reducing the load forecast (the sum of days) as compared to the reduction from the top days as a group (the optimal dispatch results). The latter is always larger.

Figure 9. Reduction ratio (R) for 1-year program, various numbers of days

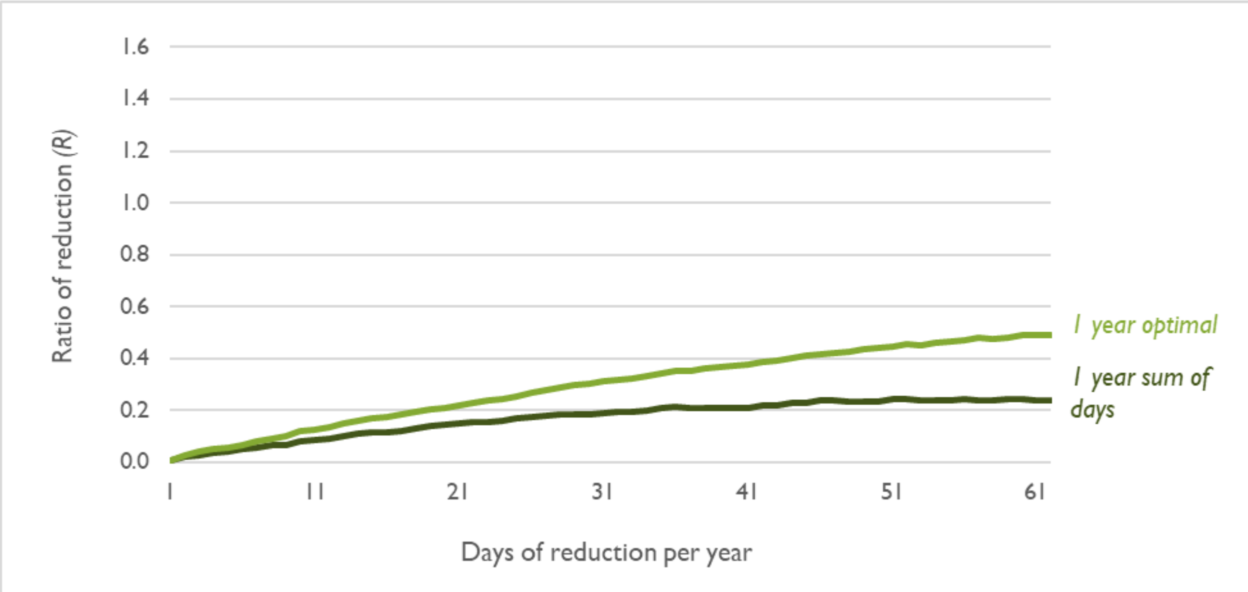


Figure 10. Reduction ratio (R) for 5-year program, various numbers of days

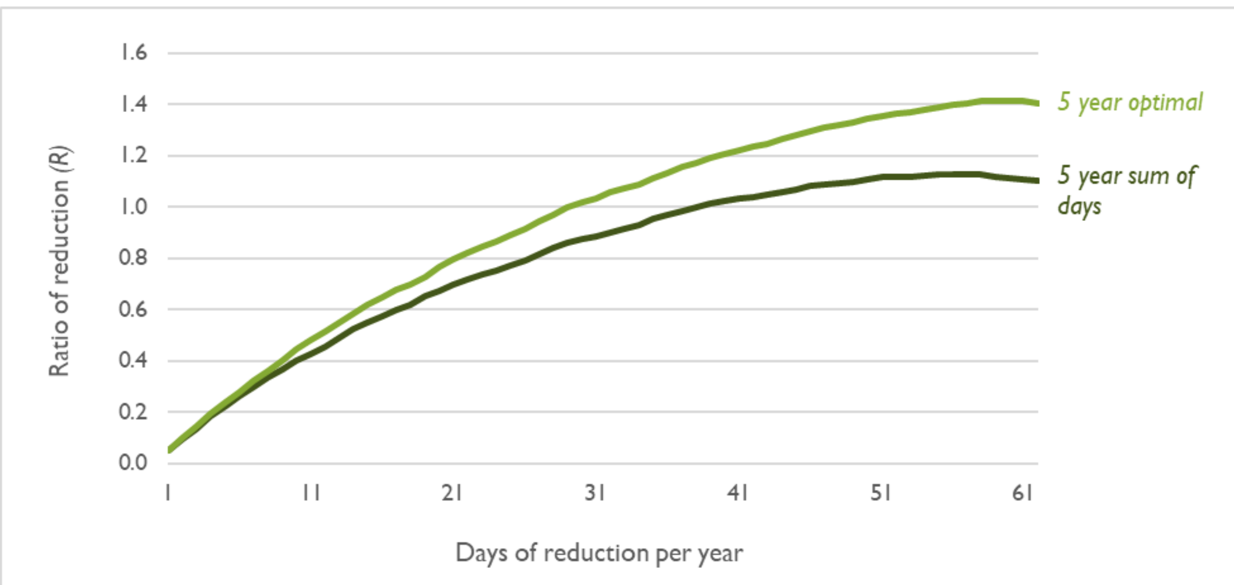
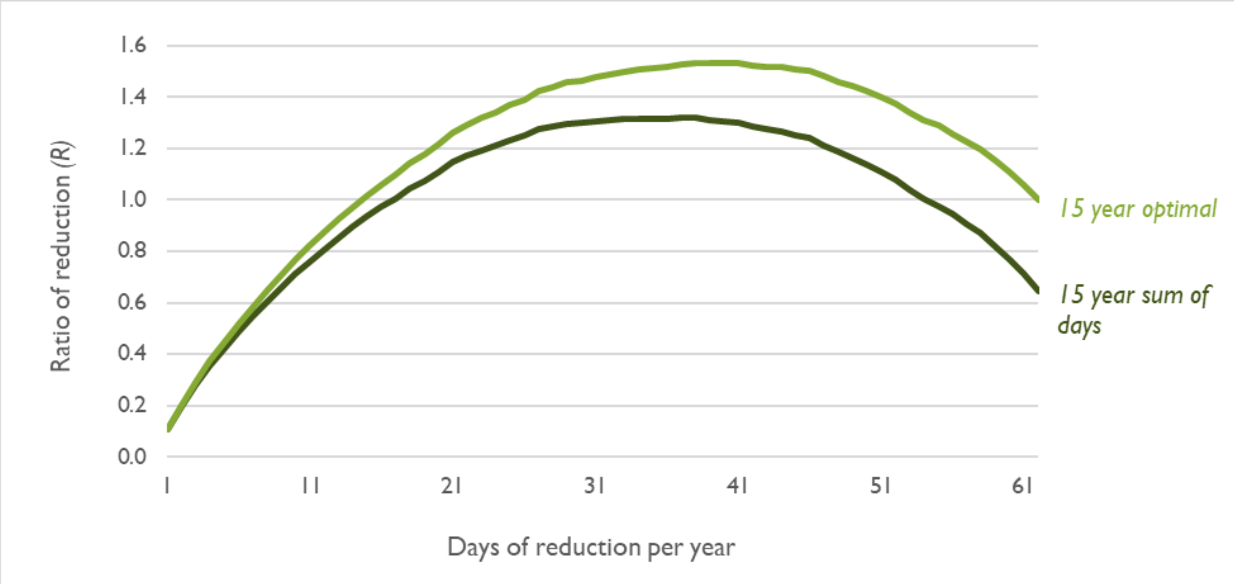


Figure 11. Reduction ratio (R) for 15-year program, various numbers of days



The question then arises, without computing the effects of reductions on all the possible combinations of days (on the order of 10^{18} possibilities), how can the effect of some set of load reductions on capacity DRIPE be estimated?

We propose that the load effect (R) for reductions on a set of days *S*, for which the lowest-load day in *S* is the *D*th highest load day of the summer, be estimated as the average of

The sum of the R values for the days in S (from Table 6, Appendix C), and

The R value for D days (from Table 4, Appendix A), minus the sum of the R values for the days less than D that are not in S (from Table 6, Appendix C).

For days 1, 4, and 5 of a one-year program (or a program that has only been running for a year), the value would be the average of

The sum of 0.009, 0.013 and 0.005, or 0.027, and

0.06 minus (0.010 + 0.006), or 0.044.

(0.027 + 0.044) ÷ 2 = 0.036.

If greater precision is necessary, or for more complex situations, for example to estimate the effect of different amounts of load reduction on different days over multiple years, we recommend repeating the regressions we describe above for the specific situation.

APPENDIX A. RATIO OF FORECAST REDUCTION TO LOAD REDUCTION

Table 4 displays the values behind Figure 6 and Figure 7, located in section 3.2. These values can be applied to capacity DRIPE values from AESC 2018 to determine new capacity DRIPE values that are specific to a demand response program.

Table 4. Ratio of forecast reduction to load reduction, by years and days/year

	Years of Reductions														
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0.01	0.02	0.03	0.05	0.05	0.06	0.07	0.08	0.08	0.09	0.10	0.10	0.10	0.11	0.11
2	0.03	0.05	0.06	0.09	0.10	0.13	0.14	0.15	0.16	0.17	0.18	0.19	0.20	0.20	0.20
3	0.04	0.07	0.10	0.13	0.15	0.17	0.20	0.22	0.23	0.25	0.26	0.28	0.28	0.29	0.29
4	0.05	0.09	0.13	0.17	0.19	0.23	0.26	0.29	0.30	0.32	0.34	0.36	0.36	0.37	0.37
5	0.06	0.11	0.16	0.22	0.24	0.28	0.32	0.35	0.37	0.39	0.41	0.44	0.44	0.44	0.45
6	0.07	0.13	0.19	0.25	0.28	0.32	0.37	0.41	0.43	0.45	0.48	0.50	0.50	0.50	0.52
7	0.08	0.15	0.22	0.29	0.33	0.38	0.43	0.47	0.49	0.51	0.54	0.57	0.57	0.57	0.58
8	0.09	0.17	0.25	0.33	0.36	0.42	0.48	0.53	0.55	0.57	0.61	0.64	0.64	0.63	0.65
9	0.10	0.19	0.27	0.37	0.40	0.47	0.53	0.58	0.61	0.63	0.67	0.70	0.70	0.69	0.71
10	0.12	0.21	0.30	0.41	0.45	0.52	0.58	0.63	0.66	0.69	0.72	0.76	0.75	0.75	0.77
11	0.13	0.23	0.33	0.45	0.48	0.55	0.63	0.68	0.71	0.74	0.78	0.82	0.81	0.80	0.82
12	0.14	0.25	0.35	0.48	0.52	0.59	0.67	0.73	0.76	0.79	0.83	0.87	0.86	0.86	0.88
13	0.15	0.27	0.38	0.52	0.55	0.64	0.72	0.78	0.81	0.85	0.88	0.93	0.92	0.91	0.93
14	0.16	0.29	0.40	0.54	0.58	0.68	0.76	0.83	0.86	0.89	0.93	0.97	0.96	0.95	0.97
15	0.17	0.31	0.43	0.58	0.62	0.71	0.80	0.87	0.90	0.94	0.98	1.03	1.01	1.00	1.02
16	0.18	0.33	0.45	0.60	0.65	0.75	0.84	0.91	0.95	0.98	1.02	1.07	1.06	1.04	1.06
17	0.19	0.34	0.47	0.63	0.68	0.78	0.88	0.95	0.99	1.02	1.07	1.12	1.10	1.08	1.10
18	0.20	0.36	0.50	0.66	0.70	0.81	0.91	0.99	1.03	1.07	1.11	1.17	1.15	1.13	1.14
19	0.20	0.38	0.52	0.69	0.73	0.84	0.95	1.04	1.07	1.11	1.15	1.21	1.19	1.17	1.18
20	0.21	0.39	0.54	0.71	0.77	0.88	0.99	1.07	1.11	1.15	1.20	1.26	1.23	1.21	1.22
21	0.22	0.41	0.56	0.74	0.80	0.92	1.03	1.12	1.16	1.20	1.24	1.30	1.27	1.25	1.26
22	0.23	0.42	0.58	0.77	0.82	0.94	1.06	1.15	1.19	1.23	1.27	1.33	1.30	1.28	1.29
23	0.24	0.44	0.60	0.79	0.85	0.96	1.09	1.19	1.23	1.27	1.31	1.37	1.34	1.31	1.32
24	0.25	0.45	0.62	0.82	0.87	0.98	1.12	1.21	1.26	1.29	1.34	1.40	1.36	1.33	1.34
25	0.25	0.47	0.64	0.84	0.89	1.01	1.15	1.25	1.29	1.33	1.37	1.43	1.40	1.36	1.37
26	0.27	0.49	0.66	0.86	0.91	1.04	1.18	1.28	1.32	1.36	1.40	1.47	1.42	1.39	1.39
27	0.28	0.50	0.68	0.89	0.95	1.07	1.22	1.32	1.36	1.40	1.44	1.50	1.46	1.42	1.42

	Years of Reductions														
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
28	0.29	0.52	0.71	0.92	0.97	1.11	1.25	1.35	1.39	1.43	1.47	1.53	1.48	1.44	1.44
29	0.30	0.54	0.73	0.94	1.00	1.14	1.28	1.38	1.42	1.46	1.49	1.56	1.51	1.46	1.46
30	0.30	0.55	0.74	0.96	1.02	1.15	1.31	1.41	1.45	1.49	1.52	1.58	1.53	1.48	1.47
31	0.31	0.56	0.76	0.98	1.04	1.18	1.33	1.44	1.48	1.51	1.54	1.61	1.55	1.49	1.48
32	0.32	0.58	0.78	1.00	1.06	1.21	1.36	1.47	1.50	1.54	1.57	1.63	1.57	1.51	1.49
33	0.32	0.59	0.79	1.02	1.07	1.22	1.38	1.49	1.53	1.56	1.59	1.66	1.59	1.52	1.50
34	0.33	0.60	0.80	1.04	1.09	1.25	1.41	1.52	1.55	1.59	1.61	1.68	1.60	1.53	1.51
35	0.34	0.61	0.82	1.06	1.11	1.27	1.43	1.54	1.58	1.61	1.63	1.70	1.62	1.54	1.51
36	0.35	0.62	0.84	1.08	1.13	1.29	1.46	1.57	1.60	1.63	1.65	1.71	1.63	1.55	1.52
37	0.35	0.64	0.85	1.10	1.16	1.31	1.49	1.59	1.62	1.65	1.67	1.73	1.65	1.57	1.53
38	0.36	0.65	0.86	1.12	1.17	1.34	1.51	1.61	1.64	1.67	1.69	1.75	1.66	1.58	1.53
39	0.37	0.66	0.88	1.14	1.19	1.35	1.53	1.63	1.66	1.69	1.71	1.77	1.67	1.58	1.53
40	0.37	0.67	0.89	1.15	1.21	1.36	1.55	1.65	1.68	1.71	1.72	1.78	1.68	1.59	1.53
41	0.38	0.68	0.90	1.17	1.22	1.39	1.57	1.67	1.69	1.72	1.73	1.79	1.68	1.59	1.53
42	0.39	0.69	0.92	1.19	1.23	1.41	1.59	1.69	1.71	1.73	1.74	1.80	1.69	1.59	1.52
43	0.39	0.70	0.93	1.20	1.25	1.42	1.61	1.70	1.72	1.75	1.76	1.81	1.69	1.59	1.52
44	0.40	0.71	0.95	1.21	1.26	1.44	1.63	1.72	1.74	1.76	1.77	1.82	1.70	1.60	1.52
45	0.41	0.73	0.96	1.23	1.28	1.46	1.64	1.74	1.75	1.77	1.78	1.83	1.70	1.60	1.51
46	0.42	0.74	0.97	1.25	1.30	1.48	1.66	1.76	1.77	1.79	1.79	1.84	1.71	1.60	1.50
47	0.42	0.75	0.99	1.27	1.31	1.49	1.68	1.77	1.78	1.80	1.79	1.84	1.70	1.58	1.48
48	0.42	0.76	1.00	1.27	1.32	1.50	1.70	1.78	1.79	1.80	1.79	1.84	1.69	1.57	1.46
49	0.43	0.77	1.01	1.29	1.33	1.52	1.71	1.79	1.80	1.80	1.79	1.84	1.68	1.55	1.44
50	0.44	0.78	1.03	1.31	1.34	1.53	1.73	1.81	1.81	1.81	1.80	1.84	1.68	1.54	1.42
51	0.45	0.79	1.04	1.32	1.35	1.55	1.73	1.82	1.82	1.81	1.80	1.83	1.66	1.53	1.40
52	0.45	0.80	1.05	1.33	1.36	1.55	1.74	1.82	1.82	1.81	1.79	1.82	1.65	1.51	1.37
53	0.45	0.80	1.06	1.34	1.37	1.56	1.74	1.82	1.81	1.80	1.78	1.81	1.63	1.48	1.34
54	0.46	0.82	1.07	1.35	1.38	1.57	1.75	1.82	1.82	1.80	1.77	1.80	1.61	1.46	1.31
55	0.46	0.82	1.08	1.36	1.39	1.57	1.75	1.83	1.82	1.80	1.77	1.79	1.60	1.45	1.29
56	0.47	0.83	1.09	1.37	1.40	1.58	1.76	1.83	1.82	1.79	1.75	1.78	1.58	1.42	1.26
57	0.48	0.84	1.10	1.38	1.40	1.59	1.77	1.83	1.82	1.79	1.75	1.76	1.56	1.40	1.23
58	0.48	0.85	1.11	1.39	1.41	1.60	1.77	1.83	1.82	1.78	1.73	1.75	1.55	1.37	1.20
59	0.48	0.86	1.11	1.40	1.41	1.60	1.77	1.83	1.81	1.77	1.71	1.72	1.51	1.33	1.15
60	0.49	0.86	1.12	1.40	1.41	1.60	1.77	1.83	1.81	1.76	1.69	1.70	1.48	1.30	1.11
61	0.49	0.86	1.12	1.41	1.41	1.60	1.77	1.83	1.80	1.75	1.68	1.68	1.45	1.26	1.06
62	0.49	0.86	1.12	1.40	1.40	1.59	1.76	1.81	1.79	1.73	1.65	1.65	1.42	1.21	1.00

APPENDIX B. RATIO OF FORECAST REDUCTION TO LOAD REDUCTION, WITH FORECAST LOAD DISTRIBUTION

Table 5 displays a modified version of the values in Appendix A, assuming imperfect dispatch. See section 3.3, subsection "Dispatching demand response with forecast load distribution" for more information.

Table 5. Ratio of forecast reduction to load reduction, imperfect dispatch

	Years of Reductions														
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0.01	0.01	0.01	0.02	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05
2	0.02	0.02	0.02	0.05	0.06	0.07	0.09	0.09	0.09	0.10	0.10	0.11	0.11	0.11	0.12
3	0.03	0.06	0.08	0.11	0.13	0.15	0.17	0.17	0.17	0.19	0.20	0.21	0.21	0.21	0.21
4	0.04	0.09	0.13	0.17	0.19	0.21	0.25	0.26	0.26	0.27	0.28	0.30	0.30	0.30	0.30
5	0.05	0.11	0.15	0.20	0.22	0.25	0.29	0.30	0.31	0.33	0.34	0.36	0.36	0.36	0.36
6	0.06	0.13	0.17	0.23	0.25	0.29	0.34	0.36	0.37	0.39	0.40	0.42	0.42	0.42	0.42
7	0.07	0.14	0.20	0.27	0.29	0.33	0.38	0.40	0.41	0.44	0.45	0.47	0.47	0.46	0.46
8	0.08	0.16	0.23	0.30	0.32	0.37	0.42	0.45	0.46	0.48	0.50	0.52	0.52	0.51	0.51
9	0.09	0.18	0.25	0.32	0.35	0.40	0.46	0.49	0.50	0.52	0.54	0.57	0.56	0.55	0.55
10	0.10	0.20	0.27	0.35	0.39	0.44	0.51	0.54	0.55	0.58	0.60	0.62	0.62	0.61	0.60
11	0.12	0.22	0.29	0.38	0.42	0.49	0.56	0.59	0.60	0.63	0.65	0.68	0.68	0.66	0.66
12	0.12	0.23	0.31	0.41	0.45	0.53	0.60	0.64	0.65	0.68	0.70	0.73	0.73	0.71	0.71
13	0.13	0.24	0.32	0.44	0.47	0.55	0.64	0.67	0.69	0.71	0.74	0.77	0.77	0.75	0.75
14	0.14	0.25	0.34	0.47	0.51	0.60	0.68	0.71	0.73	0.76	0.79	0.82	0.82	0.80	0.80
15	0.15	0.29	0.38	0.52	0.57	0.66	0.75	0.79	0.82	0.85	0.88	0.91	0.91	0.88	0.88
16	0.15	0.30	0.40	0.55	0.59	0.69	0.78	0.83	0.85	0.88	0.92	0.96	0.94	0.92	0.91
17	0.17	0.32	0.43	0.58	0.62	0.73	0.82	0.88	0.90	0.94	0.98	1.02	1.00	0.98	0.97
18	0.17	0.34	0.45	0.60	0.64	0.75	0.85	0.92	0.94	0.98	1.02	1.06	1.04	1.00	0.99
19	0.18	0.35	0.46	0.62	0.67	0.78	0.88	0.95	0.98	1.01	1.05	1.09	1.07	1.03	1.02
20	0.19	0.37	0.48	0.64	0.69	0.80	0.91	0.98	1.01	1.05	1.09	1.14	1.11	1.06	1.06
21	0.19	0.38	0.49	0.66	0.71	0.82	0.93	1.00	1.03	1.07	1.10	1.15	1.13	1.08	1.07

							Years of Reductions								
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
22	0.20	0.39	0.50	0.68	0.73	0.84	0.96	1.03	1.06	1.10	1.13	1.19	1.16	1.10	1.09
23	0.21	0.41	0.54	0.71	0.76	0.88	1.00	1.07	1.11	1.14	1.18	1.24	1.20	1.14	1.13
24	0.22	0.43	0.56	0.74	0.78	0.90	1.02	1.10	1.13	1.17	1.21	1.26	1.23	1.16	1.15
25	0.23	0.44	0.58	0.76	0.81	0.93	1.06	1.14	1.18	1.21	1.25	1.31	1.27	1.21	1.19
26	0.23	0.45	0.58	0.78	0.82	0.95	1.08	1.16	1.20	1.23	1.27	1.33	1.30	1.23	1.22
27	0.24	0.47	0.60	0.80	0.84	0.97	1.10	1.18	1.22	1.26	1.30	1.36	1.33	1.26	1.25
28	0.25	0.48	0.61	0.81	0.86	0.99	1.13	1.21	1.25	1.29	1.32	1.38	1.34	1.27	1.26
29	0.26	0.50	0.63	0.84	0.88	1.02	1.16	1.25	1.29	1.32	1.36	1.42	1.38	1.31	1.29
30	0.26	0.50	0.63	0.85	0.89	1.03	1.17	1.26	1.30	1.34	1.37	1.43	1.39	1.31	1.29
31	0.27	0.52	0.66	0.87	0.92	1.06	1.21	1.29	1.34	1.37	1.40	1.46	1.42	1.33	1.32
32	0.28	0.53	0.68	0.90	0.94	1.08	1.24	1.32	1.36	1.40	1.43	1.49	1.44	1.35	1.33
33	0.29	0.55	0.71	0.93	0.98	1.12	1.28	1.37	1.41	1.44	1.47	1.53	1.48	1.39	1.35
34	0.30	0.56	0.72	0.95	1.00	1.15	1.31	1.39	1.44	1.47	1.49	1.56	1.50	1.41	1.37
35	0.31	0.58	0.74	0.98	1.03	1.18	1.34	1.43	1.47	1.50	1.53	1.58	1.53	1.44	1.40
36	0.33	0.60	0.78	1.01	1.06	1.21	1.37	1.47	1.51	1.54	1.56	1.62	1.56	1.46	1.43
37	0.34	0.62	0.80	1.04	1.09	1.24	1.41	1.50	1.54	1.57	1.59	1.65	1.58	1.48	1.44
38	0.35	0.63	0.82	1.06	1.11	1.27	1.44	1.53	1.57	1.60	1.62	1.68	1.59	1.50	1.44
39	0.35	0.64	0.83	1.09	1.13	1.29	1.46	1.55	1.60	1.63	1.64	1.69	1.60	1.50	1.45
40	0.36	0.66	0.85	1.10	1.15	1.31	1.48	1.58	1.62	1.65	1.66	1.71	1.62	1.52	1.46
41	0.37	0.67	0.87	1.12	1.17	1.33	1.51	1.61	1.64	1.67	1.68	1.73	1.61	1.50	1.43
42	0.37	0.67	0.88	1.13	1.17	1.34	1.52	1.61	1.65	1.67	1.69	1.73	1.60	1.48	1.41
43	0.38	0.68	0.89	1.15	1.19	1.35	1.53	1.63	1.67	1.69	1.70	1.75	1.61	1.50	1.42
44	0.39	0.69	0.90	1.15	1.20	1.37	1.55	1.64	1.68	1.70	1.71	1.75	1.62	1.50	1.41
45	0.39	0.70	0.92	1.18	1.21	1.39	1.57	1.67	1.70	1.73	1.73	1.77	1.64	1.52	1.42
46	0.40	0.71	0.93	1.19	1.23	1.40	1.59	1.70	1.73	1.75	1.75	1.79	1.66	1.54	1.44
47	0.40	0.72	0.94	1.20	1.24	1.41	1.60	1.71	1.74	1.76	1.76	1.79	1.65	1.53	1.43
48	0.41	0.73	0.95	1.21	1.24	1.41	1.60	1.71	1.73	1.76	1.75	1.78	1.63	1.50	1.40
49	0.41	0.74	0.96	1.22	1.26	1.43	1.62	1.73	1.75	1.78	1.77	1.80	1.65	1.51	1.40
50	0.42	0.75	0.97	1.23	1.27	1.44	1.64	1.74	1.76	1.79	1.78	1.80	1.64	1.50	1.38
51	0.42	0.76	0.98	1.25	1.28	1.46	1.65	1.76	1.78	1.81	1.79	1.82	1.65	1.51	1.38
52	0.43	0.78	1.01	1.28	1.31	1.49	1.68	1.79	1.81	1.82	1.80	1.82	1.66	1.51	1.38
53	0.45	0.79	1.02	1.30	1.33	1.51	1.70	1.81	1.83	1.85	1.82	1.84	1.67	1.52	1.38

	Years of Reductions														
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
54	0.45	0.80	1.03	1.31	1.34	1.52	1.71	1.82	1.84	1.85	1.83	1.84	1.68	1.52	1.37
55	0.46	0.81	1.05	1.32	1.34	1.52	1.71	1.82	1.83	1.84	1.80	1.82	1.64	1.47	1.32
56	0.46	0.82	1.06	1.33	1.35	1.53	1.73	1.83	1.84	1.84	1.80	1.81	1.63	1.46	1.30
57	0.47	0.83	1.07	1.34	1.36	1.54	1.73	1.83	1.84	1.84	1.79	1.80	1.62	1.44	1.27
58	0.47	0.84	1.08	1.35	1.37	1.56	1.75	1.84	1.85	1.85	1.80	1.81	1.62	1.44	1.26
59	0.47	0.83	1.08	1.35	1.36	1.54	1.73	1.81	1.80	1.76	1.72	1.72	1.53	1.34	1.16
60	0.48	0.85	1.09	1.37	1.37	1.56	1.73	1.81	1.80	1.77	1.72	1.72	1.52	1.34	1.14
61	0.48	0.85	1.10	1.38	1.39	1.57	1.73	1.81	1.79	1.76	1.71	1.71	1.48	1.28	1.08
62	0.49	0.86	1.12	1.39	1.39	1.58	1.75	1.82	1.80	1.76	1.69	1.69	1.45	1.26	1.04

APPENDIX C. IMPACT OF INDIVIDUAL DAY LOAD REDUCTIONS

Table 6 shows our estimate of the R value (reduction in the 2021 forecast as a fraction of the annual historical load reductions), for various number of years and various numbers of days per year. See section 3.3, subsection "Daily dispatch values" for more information.

Table 6. Effect of individual day load reductions on reduction ratios

	Years of Reductions														
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0.009	0.021	0.032	0.046	0.051	0.063	0.072	0.079	0.082	0.089	0.096	0.102	0.104	0.106	0.108
2	0.010	0.021	0.031	0.040	0.046	0.056	0.064	0.073	0.078	0.081	0.081	0.086	0.086	0.086	0.087
3	0.006	0.016	0.025	0.036	0.040	0.047	0.056	0.062	0.065	0.069	0.074	0.080	0.080	0.080	0.083
4	0.013	0.024	0.035	0.046	0.050	0.056	0.063	0.069	0.070	0.067	0.081	0.083	0.075	0.075	0.077
5	0.005	0.016	0.026	0.036	0.038	0.044	0.050	0.055	0.058	0.060	0.064	0.067	0.066	0.066	0.068
6	0.011	0.014	0.020	0.038	0.041	0.046	0.052	0.050	0.052	0.053	0.057	0.061	0.059	0.058	0.060
7	0.005	0.013	0.022	0.033	0.034	0.040	0.047	0.052	0.054	0.054	0.056	0.060	0.059	0.058	0.059
8	0.007	0.022	0.024	0.035	0.036	0.045	0.052	0.055	0.056	0.059	0.060	0.062	0.062	0.061	0.063
9	0.004	0.013	0.021	0.031	0.034	0.039	0.044	0.049	0.053	0.054	0.055	0.057	0.055	0.054	0.053
10	0.012	0.014	0.021	0.032	0.030	0.038	0.043	0.047	0.048	0.050	0.050	0.052	0.051	0.051	0.053
11	0.006	0.014	0.020	0.027	0.027	0.032	0.038	0.042	0.043	0.046	0.048	0.050	0.048	0.047	0.047
12	0.004	0.013	0.020	0.027	0.029	0.035	0.040	0.045	0.047	0.049	0.050	0.051	0.050	0.048	0.049
13	0.013	0.022	0.027	0.033	0.036	0.041	0.045	0.049	0.049	0.052	0.045	0.048	0.047	0.046	0.045
14	0.009	0.010	0.017	0.023	0.031	0.028	0.033	0.037	0.038	0.038	0.039	0.042	0.039	0.037	0.043
15	0.004	0.013	0.018	0.024	0.027	0.032	0.036	0.039	0.040	0.041	0.044	0.046	0.044	0.042	0.041
16	0.002	0.010	0.016	0.022	0.023	0.029	0.033	0.036	0.037	0.039	0.039	0.041	0.039	0.036	0.036
17	0.004	0.011	0.016	0.021	0.023	0.027	0.031	0.033	0.035	0.036	0.038	0.041	0.038	0.034	0.033
18	0.009	0.012	0.023	0.024	0.023	0.027	0.031	0.036	0.036	0.037	0.037	0.039	0.040	0.038	0.037
19	0.010	0.017	0.023	0.023	0.031	0.026	0.032	0.036	0.037	0.037	0.036	0.038	0.033	0.031	0.030
20	0.006	0.012	0.012	0.018	0.020	0.023	0.029	0.031	0.034	0.036	0.037	0.039	0.037	0.034	0.035
21	0.004	0.011	0.017	0.023	0.025	0.029	0.033	0.036	0.038	0.037	0.037	0.039	0.039	0.035	0.037
22	0.004	0.010	0.014	0.021	0.019	0.022	0.025	0.028	0.027	0.028	0.026	0.027	0.024	0.024	0.026

	Years of Reductions														
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
23	0.001	0.009	0.015	0.020	0.021	0.024	0.027	0.030	0.030	0.029	0.028	0.032	0.028	0.024	0.022
24	0.007	0.012	0.010	0.015	0.014	0.016	0.019	0.022	0.022	0.022	0.028	0.023	0.019	0.016	0.019
25	0.008	0.015	0.018	0.021	0.023	0.024	0.028	0.030	0.027	0.028	0.026	0.027	0.024	0.023	0.021
26	0.006	0.013	0.018	0.016	0.018	0.021	0.026	0.028	0.027	0.026	0.026	0.027	0.023	0.019	0.018
27	0.005	0.012	0.017	0.024	0.025	0.027	0.030	0.032	0.031	0.031	0.031	0.031	0.028	0.027	0.025
28	0.003	0.009	0.021	0.021	0.025	0.024	0.026	0.032	0.025	0.024	0.021	0.021	0.017	0.013	0.009
29	0.001	0.008	0.013	0.017	0.017	0.023	0.026	0.026	0.025	0.025	0.023	0.023	0.022	0.016	0.012
30	0.002	0.009	0.012	0.015	0.015	0.017	0.021	0.021	0.020	0.020	0.018	0.017	0.013	0.008	0.003
31	0.002	0.013	0.016	0.014	0.013	0.016	0.019	0.021	0.020	0.020	0.019	0.019	0.014	0.009	0.005
32	0.008	0.007	0.010	0.015	0.015	0.016	0.020	0.021	0.021	0.020	0.017	0.018	0.014	0.010	0.005
33	0.000	0.005	0.007	0.011	0.012	0.015	0.018	0.020	0.020	0.019	0.018	0.018	0.012	0.009	0.005
34	0.006	0.005	0.013	0.018	0.018	0.021	0.024	0.025	0.024	0.023	0.013	0.013	0.008	0.005	-0.001
35	0.009	0.015	0.018	0.022	0.021	0.017	0.019	0.018	0.016	0.016	0.013	0.013	0.008	0.005	0.000
36	0.002	0.006	0.010	0.015	0.015	0.016	0.019	0.018	0.016	0.015	0.013	0.012	0.008	0.004	0.002
37	-0.001	0.006	0.009	0.014	0.015	0.018	0.020	0.018	0.016	0.015	0.014	0.014	0.009	0.007	0.002
38	-0.001	0.005	0.007	0.018	0.018	0.015	0.016	0.016	0.016	0.015	0.013	0.012	0.009	0.005	-0.001
39	0.000	0.005	0.008	0.011	0.010	0.012	0.014	0.012	0.012	0.011	0.010	0.008	0.002	0.000	-0.006
40	-0.001	0.005	0.009	0.012	0.010	0.010	0.013	0.013	0.012	0.010	0.008	0.008	0.002	-0.002	-0.008
41	0.001	0.006	0.009	0.011	0.011	0.014	0.015	0.014	0.012	0.012	0.010	0.008	0.002	-0.002	-0.006
42	0.008	0.005	0.008	0.010	0.008	0.010	0.012	0.010	0.008	0.005	0.003	0.002	-0.004	-0.008	-0.015
43	0.001	0.005	0.006	0.007	0.008	0.012	0.013	0.013	0.010	0.008	0.006	0.004	0.000	-0.003	-0.010
44	0.008	0.013	0.007	0.016	0.011	0.013	0.015	0.012	0.011	0.010	0.007	0.006	0.003	-0.001	-0.008
45	0.001	0.005	0.007	0.009	0.009	0.011	0.012	0.009	0.006	0.003	0.003	-0.001	-0.007	-0.009	-0.016
46	0.007	0.005	0.008	0.011	0.012	0.012	0.015	0.014	0.011	0.009	0.008	0.005	-0.001	-0.006	-0.011
47	0.001	0.005	0.009	0.010	0.009	0.011	0.011	0.008	0.005	0.001	-0.004	-0.007	-0.013	-0.019	-0.026
48	-0.001	0.003	0.004	0.005	0.002	0.004	0.009	0.007	0.005	0.001	-0.002	-0.004	-0.011	-0.018	-0.026
49	-0.002	0.003	0.008	0.011	0.008	0.009	0.008	0.006	0.003	-0.001	-0.005	-0.007	-0.013	-0.018	-0.023
50	0.001	0.004	0.007	0.008	0.007	0.009	0.007	0.005	0.004	-0.001	-0.004	-0.008	-0.012	-0.018	-0.026
51	0.007	0.011	0.014	0.013	0.010	0.012	0.009	0.006	0.004	-0.005	-0.008	-0.011	-0.018	-0.023	-0.031
52	-0.001	0.002	0.003	0.003	0.000	0.001	-0.001	-0.001	-0.004	-0.009	-0.011	-0.013	-0.019	-0.024	-0.029
53	-0.002	0.001	0.002	0.003	0.001	0.001	-0.001	-0.005	-0.008	-0.013	-0.018	-0.021	-0.026	-0.033	-0.041

	Years of Reductions														
Days	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
54	0.000	0.004	0.004	0.005	0.003	0.002	0.000	-0.003	-0.007	-0.010	-0.015	-0.019	-0.024	-0.027	-0.034
55	-0.002	0.002	0.003	0.006	0.003	0.005	0.003	0.003	0.001	-0.005	-0.008	-0.010	-0.016	-0.021	-0.027
56	0.004	0.001	0.003	0.004	0.001	0.000	-0.001	-0.005	-0.007	-0.013	-0.019	-0.023	-0.021	-0.027	-0.034
57	-0.001	0.001	0.003	0.003	0.000	0.000	0.000	-0.003	-0.005	-0.010	-0.013	-0.018	-0.024	-0.030	-0.038
58	-0.002	0.001	0.002	0.003	0.000	-0.001	-0.003	-0.008	-0.010	-0.013	-0.018	-0.021	-0.025	-0.029	-0.036
59	0.004	-0.001	-0.001	-0.001	-0.006	-0.007	-0.009	-0.011	-0.014	-0.021	-0.028	-0.032	-0.039	-0.045	-0.051
60	0.002	0.004	-0.002	-0.001	-0.004	-0.003	-0.004	-0.008	-0.011	-0.017	-0.024	-0.028	-0.035	-0.042	-0.050
61	-0.005	-0.003	0.006	-0.001	-0.005	0.002	-0.007	-0.009	-0.004	-0.018	-0.025	-0.029	-0.038	-0.047	-0.055
62	0.000	-0.001	-0.002	-0.003	-0.009	-0.013	-0.014	-0.018	-0.022	-0.029	-0.037	-0.040	-0.048	-0.058	-0.068