Load Control Analysis for Intermittent Generation Mitigation

David P. Chassin, Pacific Northwest National Laboratory

Abstract – Load control has always been a part of the repertoire of resources used by utilities to manage the balance between electric energy supply and demand. In recent years, advances in communications and control technology have enabled utilities to consider continuously controlling demand response to mitigate intermittent generation. This paper discusses a general method for load resource analysis that parallels an approach used to analyze intermittent generation resources and might help understand how demand response control can be examined in a manner consistent with generation control.

Keywords: load management, load shedding, load modeling, wind power generation.

1. Introduction

The standard method of control for interconnected electric power systems involves continuous control of generation to follow load. These controls are augmented with control of fast acting devices such as shunt and series devices to manage system voltage and frequency to desired operating points. Even in extreme situations, load control and ultimately load shedding are retained only as measures of last resort, the obligation to serve being the paramount duty of the system operators. Whether system control is based on generator speed governor feedback or area generation control [1], the conventional focus of control is on the supply side of the system and not the demand side.

There has nonetheless been a longstanding interest in using load to assist in managing the balance of supply and demand in power systems. Time-of-use rates have been used for many decades to help reduce load during peak periods, although such economic measures are not generally regarded as load control per se, rather a mechanism that encourages consumer behavior through indirect economic signals that lead to load reduction at propitious times. Load control through real-time pricing has been described [2] and demonstrations of real-time price systems using bidding strategies have been demonstrated successfully [3].

Direct load control has consistently demonstrated a measurable impact on load behavior. It is well known that thermostatically controlled loads in particular are more amenable to load curtailment strategies, but that these strategies often have potentially adverse delayed effects such as demand rebound [4], consumer fatigue [5] and free-rider behavior [6]. Direct control of small numbers of large on/off loads has long been known to not achieve the same results as proportional control [7]. This has necessitated careful design of direct load control systems such that sufficient numbers of participants provide an adequate equivalent capacity [8] and that control actuation does not disrupt daily load diversity patterns or result in control of loads for too long [9]. Smart grid operations concepts have led to a growing interest in continuous control of load to follow generation, with attendant concerns about stability, controllability and observability and the resulting pressure to improve load models, control designs, and metering systems [10].

The growing use of load control for purposes other than peak load reduction has created a growing need for models of load behavior that show higher fidelity. There are already a wide range of potential applications of load control models, including forecasting, billing, program cost/benefit analysis, measurement and verification, customer classification, and unit-commitment and economic dispatch. In addition enhanced load models that include sub-hourly dynamics are used for load synthesis to provide more accurate power system simulations [11] control design to provide more accurate plant models for feedback loops, as well as optimal control, load relief, load transfer, and contingency analysis.

Most recently load control has been proposed to mitigate wind and solar intermittency [12]. However these proposals require more advanced models of load and load controls to address the stability, resource adequacy and economic considerations that typically arise when the power system controls are modified. This problem is especially challenging because conventional load control dispatch has essentially been one-time curtailment signals. Real-time price control systems use continuous signals and there is every reason to believe that only closed-loop control systems will be safe to operate on a large scale. Consequently, it seems we require a more general and integrated approach to modeling load control systems. Even though in the short term such a model may not address all the concerns raised, it is hoped that the approach proposed in this paper can lead the electric power industry to employ a more diverse and better integrated portfolio of regulation resources.

This paper 1) makes the case for why time-domain models of loads do not necessarily help understand the behavior of load control systems; 2) examines an approach to modeling demand response in the frequency domain; and 3) presents a geometric interpretation to aid in understanding the relationship of cyclic load to intermittent generation. The model is then tested on the results of a field study of demand response control using prices. Finally a general discussion of the implications of such a model is presented.
2. Load Resource Modeling

Traditionally, demand response behavior analysis has focused on load resource performance metrics such as peak reduction, energy use changes, and the time over which demand response behavior can be sustained using load control systems. However, from an analytic standpoint, these methods fail to provide the deep insight into the relationship between the control system, the controlled system, or the relationship between the input (e.g., generation intermittency) and the output (e.g., net load) that is associated with methods like those used for control systems analysis.

FERC identifies demand response as a potentially quantifiable, reliable resource for regional planning purposes [17]. FERC defines demand response as “changes in electric usage by demand-side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized,” and “can help reduce electric price volatility, mitigate generation market power, and enhance reliability.” FERC Order 1000, issued in July 2011 reinforces Order 890’s requirement for public utilities and transmission providers to consider all types of resources, including demand response, on a comparable basis in regional transmission planning.

Unfortunately, FERC does not identify a rigorous method for identifying, quantifying or measuring demand response, except in the economic sense, i.e., demand elasticity that mitigates price volatility at high-load, which forces system planners to devise various methods for themselves. For example, PG&E presents demand response to their customers as programs “designed to be both fiscally and environmentally responsible ways to respond to occasional and temporary peak demand periods.” [18] Similarly, the Northwest Power and Conservation Council defines demand response potential in terms of the available “conservation measures that cost less than the marginal generating resource.” [19] Most of these definitions fail to rigorously address the question of whether the resources are available or deployable when they are needed.

The challenge for transmission planning is that system operators are not generally comfortable placing their faith in economic systems without some basis for understanding how the economic strategies interact with the control systems that regulate the balance between supply and demand at time scale shorter than those effected by markets. This is particularly the case when considering very large scale load control strategies based on price signals, as opposed to load control systems based on load control aggregation services.

For load models to be useful in the study of power systems control, they should represent the aggregate behavior of loads in a manner that elucidates the relationship between how much power is consumed (magnitude), when it is consumed (phase) and how often (frequency), all of which can be examined coherently in the frequency domain. Aggregate load modeling has been historically challenging and typically focuses on the composition of load by end-use class [13]-[15] and sometimes on the frequency domain models of individual end-uses. But aggregate models of all end-uses combined have only rarely been addressed in the frequency domain [16] and then not for the purpose of identifying or controlled demand response resources.

A frequency-domain approach that may be more conducive to answering questions about the behavior of load control systems can be summarized as follows. Let \( L(t) \) be the load observed at the times \( t \) between 0 and \( T \), which we refer to as the load shape. The transform of \( L \) is referred to as the load profile:

\[
\hat{L}(s) = \int_0^T L(t) e^{-st} dt,
\]

where \( s = \omega = 2\pi f \) are the frequency components of the loads’ periodic behaviors. The distinction between load shape and load profile is strictly a matter of recommended convention—the former being in time domain and the latter in frequency domain—because historically the two terms have been used interchangeably. The underlying information is the same so that except for the domain of the function, the two terms refer to an identical property of the end-use load, which is simply presented differently.

All loads, whether controlled or not, are fundamentally periodic in nature. Although many loads may be periodic in trivial ways or at useless frequencies, there may be enough load that is periodic in ways that can mitigate generation intermittency to make the potential for demand response significant and worth quantifying in a rigorous manner, regardless of whether it controlled directly or influenced by a price signal. Moreover, although a single load may not be itself obviously periodic, in the aggregate a group of loads may always be decomposed into a groups of load or generation behaviors that are periodic.

For example, thermostatic loads under non-intrusive control such as thermostat offset or duty cycle control have a maximum benefit that can be derived from curtailment, which is the amplitude of the load over the period during which it operates. A load that is shifted within the time horizon \( T \) is displaced in time so that both its primary function and its rebound fills a subsequent load valley making the overall load “flatter”. (If the load is deferred beyond the time horizon \( T \), the peak is nonetheless mitigated even though the rebound is outside the observations in the interval of \( T \).)

It is very helpful to make a distinction between demand variability that is controllable and all demand variability observed. The demand variability observed through this analysis is always greater than or equal to the variability that is controllable. Thus, any observation of demand variability is always greater or equal to the controllable demand response and is the basis for estimating the maximum potential for the load to serve as a demand response resource. Furthermore, the point at which the measurements of demand variability are observed may help identify those that are potentially controllable. For example, utility feeders are often distinguished by the class of customers connected, with varying numbers of residential, commercial, industrial and
Agricultural consumers connected. Because each customer class can be expected to have a distinct load composition, different fractions of the variability observed can be expected to contribute to the controllable demand.

A similar analysis has been already applied to intermittent resources [20], where \( G(t) \) is the generation shape observed at the times \( t \) from 0 to \( T \), and \( \hat{G}(s) \) is the generation profile at the frequency components \( s \), even though the driving functions are different for generation intermittency than they are for load response. The potential for demand response through load shifting to offset the resource intermittency is thus found by examining the vector sum \( M = G + L \). In the time domain \( M(t) \) describes the net power required to satisfy the controlled load given the intermittent generation available at the time \( t \).

In the frequency domain \( \hat{M}(s) \) describes both the magnitude and timing of the combined generation and load at the frequency components \( s \). This is illustrated in Figure 1 for a single frequency component \( s \) of generation \( G \) and load \( L \).

![Figure 1. Load L cycling combined with generation G intermittency to create the net load M at the frequency component s in the complex plane, with the load delay \( \theta \) less than the net load delay \( \phi \).](image)

The present model necessitates the convention that angle 0 be the ascending zero crossing of the real part. Thus when generators and loads are in phase, they have the same angle and the same sign. For all phase angle differences \( \theta(s) = \angle \hat{L}(s) - \angle \hat{G}(s) \) the total power magnitude of the combined system at the frequency component \( s \) is found by the relation

\[
|\hat{M}(s)|^2 = |\hat{L}(s)|^2 + |\hat{G}(s)|^2 - 2|\hat{L}(s)||\hat{G}(s)|\cos[\pi - \theta(s)]. \tag{2}
\]

When the phase angle difference \( \theta \) between the generation and load is zero, the load varies in phase with the generation and the ability for load to respond to changes in generation is at its maximum. As the phase difference increases, fractionally more load must be shifted at any given frequency to compensate for a given change in generation. In the limit, when \( \theta \) is \( \pm \pi \) the load is completely out of phase and the demand response potential is at its minimum.

The significance of the phase differences is crucial to understanding the relationship between potentially controllable load and intermittent generation. One should think of the angle difference as representing the time lead or lag (at a particular frequency) between when the load peaks and when the generation peaks. A positive phase angle means that the load peaks lag the generation peaks, and a negative phase angle means the load peaks lead the generation peaks. The actual time lead/lag is simply \( \phi/\omega \). Thus shifting the phase angle through load control strategies amounts to adjusting the numerator of lead/lag relationship of supply and demand at the frequency component \( s \). Similarly, duty cycle control of loads adjusts the denominator.

This model leads to a more rigorous and more general definition of demand response than those provided above: demand response is any combination of changes in load frequency, magnitude and phase that result in a change in the overall load shape in a system.

Consider a demand response control strategy that satisfies the precondition that no change is permitted in \( M \) at any frequency component \( s \). This implies that any change in the magnitude \( G \) can only be counteracted by a change in the magnitude and angle of \( L \). This condition is illustrated in Figure 2 and is described by the equations

\[
\begin{align*}
\text{Re} \hat{L}'(s) &= \text{Re} \hat{L}(s) - \left|\hat{G}(s)\right| + \left|\hat{G}'(s)\right| \\
\text{Im} \hat{L}'(s) &= \text{Im} \hat{L}(s)
\end{align*}
\tag{3}
\]

The part of the load that responds to a change in generation is the active or responsive load and the part that cannot respond to a change in generation is the latent or unresponsive load. It is fundamental to observe that the cyclic nature of the loads implies that these parts are not directly additive, i.e., the responsive load plus the unresponsive load is always greater than the total load.

According to this particular example of load control, the generation intermittency phase angle and the frequency of the load behavior are fixed. When the generation intermittency angle or the load cycling frequency changes, we must consider those changes as well when determining the response of the load, a question that can be much more clearly elucidated using this model but is beyond the scope of this paper.
3. Application of Method

We can test this model by using it to re-examine the results from the Olympic Peninsula Demonstration project. This field test of load control included a real-time price (RTP) based load control systems that incorporated a retail double-auction for feeder capacity based on the wholesale hourly Mid-Columbia price of energy to affect duty-cycle and load shifts. Thus the relationship of this load to a hypothetical intermittent wind generation situation can be examined using the model presented.

This demonstration used measurements taken at the feeder. While there is not requirement arising from the model itself that dictates where measurements must be taken, one should expect that the control system designed for the load control might give rise to constraints on where measurements of load might be taken.

Figure 3 presents the duration curves of total residential load, available RTP-controlled load, and wind generation resources for the period from May through December 2006 (the period for which wind power data was available). For the same period, Figure 4 presents the independent duration curves of the available load control resources according to the frequency at which they vary naturally, ranging from 180 minutes down to 30 minutes. The values presented are the amplitudes at key frequencies observed over the time series of the entire project but presented as a duration curve (i.e., sorted in descending order of magnitude). Figure 5 similarly presents the relative magnitude of the load control resource duration curves according to whether they could be used for energy (MW.h), capacity (MW), or ramping (MW/h) response using the methods based on the relationship between ramping, load, and energy described in by Makarov et al. [21].

Figure 6 compares the load-controlled customers under RTP rate with customers in the experimental control group (Control) who did not receive price-based load control signals. The comparisons are made at the key frequencies over which load control effects on demand response can be observed, i.e., 24h, 12h, 6h, 3h, 2h, and 1h. The analysis was performed using a fast-Fourier transform over 15 minute load samples collected from individual homes with daily analysis windows over the duration of the project.

These results illustrate how load control systems behave differently under varying conditions. For example, at the 24 hour period, load control shows in increase in the magnitude of the load during key heating peaks. This occurs when preheating/recovery strategies are employed and consumers allow an increase in the diurnal fluctuations of indoor temperature relative to morning/evening period fluctuations. This is most pronounced relative to the 12 hour period, which shows a marked decrease in amplitude over the entire heating season. In effect, the two peaks of the 12 hour period (morning and evening) shift in opposite directions and merge to become a single 24 hour peak in the middle of the night, as shown in the reported results of project.

Similarly, the 6 hour seasonal shift observed should not be interpreted as a shift of load from one season to another, but as a shift of load away from the 6 hour period toward other periods during the summer and toward the 6h period from other periods during the winter. This behavior can be best understood if one considers that price fluctuations in the summer differ from those in winter and these fluctuations would potentially enhance or suppress the natural periodic behavior of load during those times, depending on whether they vary sympathetically with the periodic behavior of price.
Figure 3. Total load (red), wind generation (blue), and controllable load (black) as duration curves.

Figure 4. Load resource magnitudes at observable frequencies as duration curves.

Figure 5. Energy (puMW.h), capacity (puMW), and ramping (puMW/h) as duration curves.

Figure 6. Annual variations of load response magnitudes in kW for various frequencies components.
4. Discussion

The use of the Laplace transform may not be ideal for all the types of waveforms that are observed in loads. However, the Laplace transform is well suited to those loads whose periodic behavior is amenable to control. In addition, one must recognize that many loads are either not periodic at relevant frequencies (e.g., “snow-bird” occupancy), or their periodic behavior is strongly driven by externalities that do not allow them to be controllable in useful ways (e.g., commercial building ventilation-driven cooling loads). These loads would be visible in the frequency domain analysis as potential demand response, but would not expected to contribute to the demand response were they not controlled. Ultimately, the determination of which loads actually contribute demand response is based on the control system, not of the observation of the potential itself. The potential can only be used to determine maximum potential available from frequency or phase shifts in the load.

One might be tempted to repeat this analysis for energy storage and ramping applications of load control. However, the relationships of these three load responses to the load shape make this unnecessary. Aside from conservation behavior (which affects load behavior at frequency components much lower than those observed here), it is easy to relate the energy control of load (e.g., storage-like behavior) to the integral of the load control (e.g., capacity-like behavior). Similarly, load response is itself the integral of the ramping control (e.g., regulation-like behavior) as shown in Figure 5.

These relationships are represented in the time domain as

\[ \int_{0}^{T} R(t) dt = L(t) = \frac{d}{dt} E(t), \quad (4) \]

and in the frequency domain they are [21]

\[ \frac{1}{s} \hat{R}(s) = \hat{L}(s) = s \hat{E}(s). \quad (5) \]

This leads us to make a general observation about load behavior: there are not three separate behaviors (e.g., storage, capacity, and ramping) but only a single behavior that can be expressed in three distinct ways depending on the design of the load control system. Combined, the behavior of all three types of demand response is more properly expressed as

\[ \hat{D}(s) = \left( \frac{1 + s + s^2}{s} \right) \hat{L}(s). \quad (6) \]

It seems unnecessary to separately observe or analyze the energy or ramping behavior of loads as something distinct from power demand behavior; observing only one of the behaviors is sufficient to deduce the other two. In fact, the frequency domain representation of each allows us to more clearly consider the interplay of load phase angles and magnitudes at various frequencies relative to intermittent generation, and more readily treat problems related to the joint control of all three applications of load control. Merging these behaviors can obscure the true model of loads, but it has the advantage of incorporating all the types of demand response into a unified model.

Two essential features of this model are noteworthy. First, for certain types of loads, the control bandwidth may be much larger than the Gabor limit. The range of frequencies over which the model applies may not be amenable to treatment as a single frequency \( s \) so that the response should be considered over an integral of frequencies rather than individual frequency components and load shifting constraints may be shared among frequencies. Similarly, the measurement system may not satisfy the Nyquist frequency limit and control at frequencies outside this limit may not be possible.

The particularity of the relation between the angle of the generation intermittency and the load cycling at any particular frequency component \( s \) impose important limits to the amount of demand response that may be available. If the phase angle of the load cycle is 90° leading or lagging the generation intermittency, then the load is entirely latent and there is no part of the load that can be made to respond to a change in generation at that frequency component. This constraint may be quite severe for certain end-uses and in practice may preclude shifting the load for intermittent generation mitigation, depending on prevailing conditions and the properties of the load control system.

Given the load control methods that can be examined using this model, a relatively simple method for maximizing the demand response resources available to mitigate generation resource intermittency could be devised as follows:

1) After the generation and load forecasts are obtained, shift the loads at each frequency \( s \) such that their phases maximize the demand response potential with respect to the forecast uncertainties.

2) For each deviation in magnitude of the generation resources, adjust the phase of the load to minimize the deviation.

Any general approach to scheduling of load as a demand response resource must consider the basic characteristics of the intermittent resources it balances and the possible errors in the forecast. For example, if a solar forecast calls for a relatively cloudless day, then the schedule of the load should be completely in phase with the PV units because the solar output is much more likely to decrease than increase. Conversely, if the forecast calls for an largely overcast day, then the loads should be scheduled such that they are out of phase and in the event of an unanticipated increase in solar output, the loads can be brought into phase. This approach can be expected to increase the available demand response resource available to as much as 200% of the magnitude of the load under control.

It is very important to recall that this approach is not limited to only thermostatic loads where control hysteresis is the basis for shifting demand. Because most every varying load is fundamentally periodic in nature, most every varying load is potentially subject to this treatment even if it is not necessarily controllable yet. The only distinction is whether
the load control system presents any significant response in the band of frequencies at which response is desired.

Finally, it will be important to any broad generalization of this approach to address the manner in which load diversity and indeed the stochastic nature of both load and generation is expressed using this model. Load diversity for cycling loads is expressed both in the distribution of load magnitudes and the distribution of load phase angles. The effects of various distributions of both should be examined in future papers.

5. Conclusions

This paper has examined the methods, values and application of analysis load behavior in the frequency domain. Energy, capacity, and ramping responses are shown to be simply various aspects of the same behavior. The limits of load control systems that shift the relative timing of cyclic loads but do not reduce overall energy consumption have been established in a more rigorous manner than time-domain analysis methods easily allow. The analysis method was applied to results from a price-based load control demonstration pilot study and provided insights that were heretofore not available.

The method suggests ways in which aggregate load models can be incorporated into load control system models. Significant work is still required to understand and enhance the applicability of this model to demand response control systems when they are used to mitigate intermittent generation, particular when price-based control strategies are employed.

References


