> Itron white paper

Incorporating DSM into the Load Forecast

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Introduction

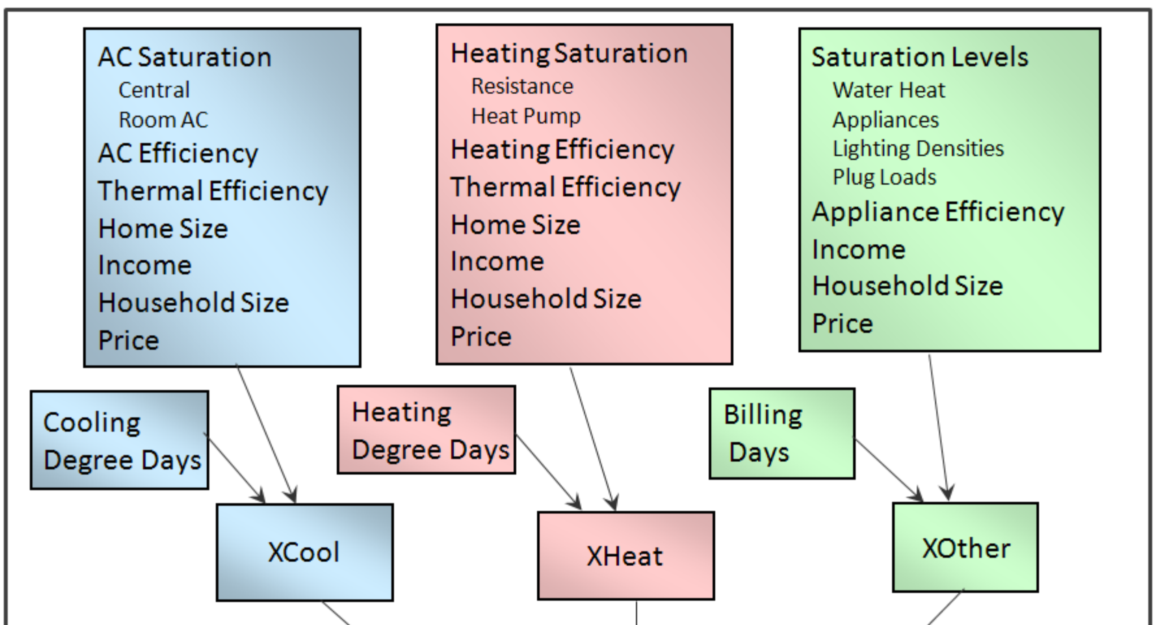
Since 1970, Demand Side Management (DSM) programs have been used to reduce energy demand growth. These programs include measures to increase conservation levels, improve energy efficiency, and deploy load management techniques. With today's focus on environmental issues and energy independence, companies and policy makers are renewing their interest in DSM programs. Recently, several utilities and government agencies have set accelerated DSM targets for future years.

The purpose of this paper is to discuss methods for adjusting load forecasts to account for DSM programs. This paper begins with an overview of current industry forecasting practices and highlights key DSM accounting issues. This is followed by a discussion of methods that can be applied to the econometric modeling frameworks used throughout the electric industry.

Energy Forecasting Methods

Each year, utilities forecast sales for budget and planning purposes. The process typically includes forecasting monthly sales by rate class using an economic model driven by weather and economic variables. More recently, many utilities have adopted Itron's Statistically Adjusted End-Use (SAE) modeling approach to include greater end-use information into the forecast process. This approach is depicted in Figure 1.

Figure 1: General Depiction of SAE Method



$$\text{Load}_t = a + b_c \times \text{XCool}_t + b_h \times \text{XHeat}_t + b_o \times \text{XOther}_t + e_t$$

The SAE approach begins with regional estimates of end-use saturation levels, average efficiency levels, thermal efficiency levels, and end-use energy estimates in a reference year. These estimates are developed from analysis provided by the U.S. Energy Information Administration (EIA). For each end-use, these data represent the average efficiency of the appliance stock in place in each year. The average efficiency forecasts are based on technology level analysis about the range of efficiency levels available in the market, assumptions about how this range is expected to evolve in the forecast period, and assumptions about how efficiency standards will limit the range. The analysis proceeds with stock accounting to bring the new equipment into the mix of existing equipment, resulting in a forecasted time-path for average efficiency values.

Although EIA efficiency data are typically used, regional data are often adjusted or replaced to agree with utility data from local saturation surveys. In addition, energy consumption levels by end-use are adjusted to agree with use-per-customer data and aggregate weather sensitivity of the local utility. These data are then used to construct aggregate end-use variables, XCool, XHeat, and XOther.

The general equation for the SAE model is shown at the bottom of Figure 1. In this equation, XHeat, XCool and XOther are structured variables that account for saturation levels, average efficiency levels, and usage trends of end-use categories in an econometric framework. Once these X variables are computed, the econometric equation calibrates the end-use inputs to the historical sales data for the utility and the monthly sales forecast is created.

DSM Forecasting Issue

When applying the SAE framework, DSM activity is naturally incorporated in the efficiency assumptions and the calibration to historic sales data. Efficiency assumptions incorporate national level DSM impacts. Calibration incorporates specific utility DSM impacts.

In the underlying analysis for the efficiency assumptions, model parameters and hurdle rates used in technology choice modeling are calibrated based on efficiency levels implied by new appliance shipment data. To the extent that these observed market outcomes reflect DSM activity at the national level, the efficiency forecasts embed the historical levels of DSM. For example, when DSM programs reflect the purchase of above-standard options, the model parameters are calibrated to these market outcomes. As a result, there is an implicit assumption that future outcomes will continue to be influenced by continued program activity promoting purchase of options that are better than standards.

In the final calibration of the SAE variables to historic sales data, model coefficients are fit to historic data that may have been impacted by utility specific DSM programs. To the extent that a utility has implemented DSM programs in the past, these programs' savings would be embedded into the sales history by lowering sales. Any economic projection of the sales history will contain the implicit assumption that comparable programs will be operated in the future.

Because DSM impacts are embedded in the SAE framework, we must consider how to modify the SAE framework to account for historic and future DSM. This discussion begins with an overview of DSM impact accounting and the data required by the forecaster.

DSM Impact Accounting

The business case for future DSM programs is typically developed through a market assessment. The assessment provides estimates of market potential for energy savings at the technology level. The assessments are ultimately translated into programs to promote efficient technologies. Program planning includes assumptions about technology impacts, measure life, and adoption levels. Finally, the assumptions are translated into a stream of costs and benefits in the form of energy savings and the value of these savings.

Once a program is implemented, participation levels are monitored, and initial impacts are estimated based on these levels. The success of the implemented program is measured through program evaluations. Topics in an evaluation study include program processes, participation levels, free rider rates, and estimation of the actual energy impacts achieved for program participants.

The primary need for the load forecaster is a year-to-year or month-to-month series that can be used in the SAE modeling framework. Both the initial program assessments and the completed program evaluation studies are useful for developing the data series required by the forecaster in order to incorporate DSM into the load forecast.

Program Impact Streams

Each year as programs are implemented, the impacts are estimated based on participation levels. This is depicted in Figure 2 which shows the time stream of impacts (energy savings) from three years of program activity. Year A programs, shown in blue, have partial impacts in the first year (Year 1) and full impacts in subsequent years (Year 2 to Year 6). Based on measure life assumptions, the impacts ramp down in Year 7 and Year 8. There are no impacts for the Year A programs in Year 9 and 10. Year B programs, shown in red, have partial impacts in the initial year (Year 2), followed by a similar stream of impacts to the right (Years 3 to 9). Year C programs, shown in orange, finish the picture, with initial impacts beginning in Year 3.

Cumulative Program Impacts

The forecaster has no direct interest in the accomplishments of individual programs or the first-year impact of programs. The relevant question involves how much energy sales are reduced in each year from the combination of all programs run from a point in time. For the discussion of modeling methods, this is the **cumulative impact**. As shown in Figure 2, the cumulative impact of programs in any year is the vertical sum across program years of the continuing impacts of these programs. For example, in Year 3, the cumulative impact of Programs A, B, and C is represented by the blocks labeled A3 + B2 + C1.

Note, that the term "cumulative" is also used in some cases to represent the stream of impacts from programs in a given year (e.g., A1 + A2 + … + A7). This is the stream that would be discounted to a present value to calculate benefit/cost ratios. In the forecasting discussion, this paper will attempt always to use the term cumulative to mean the vertical sum of the impacts in a year, not the horizontal sum of an impact stream over time.

Figure 2: Illustration of Impact Accounting and Aggregate Impacts

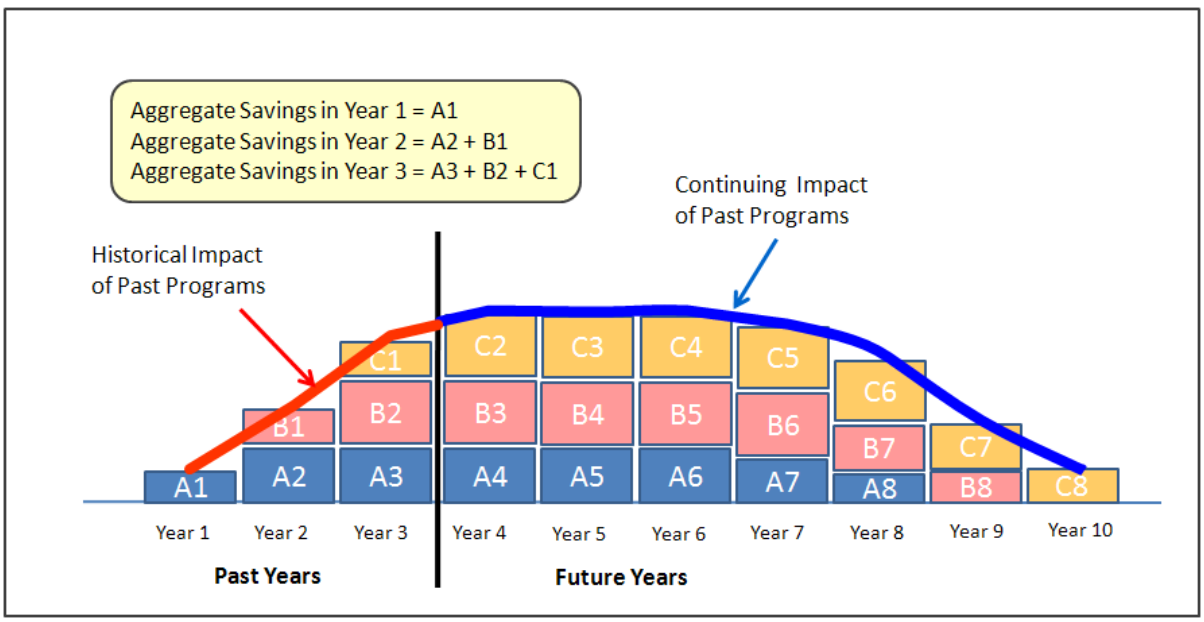
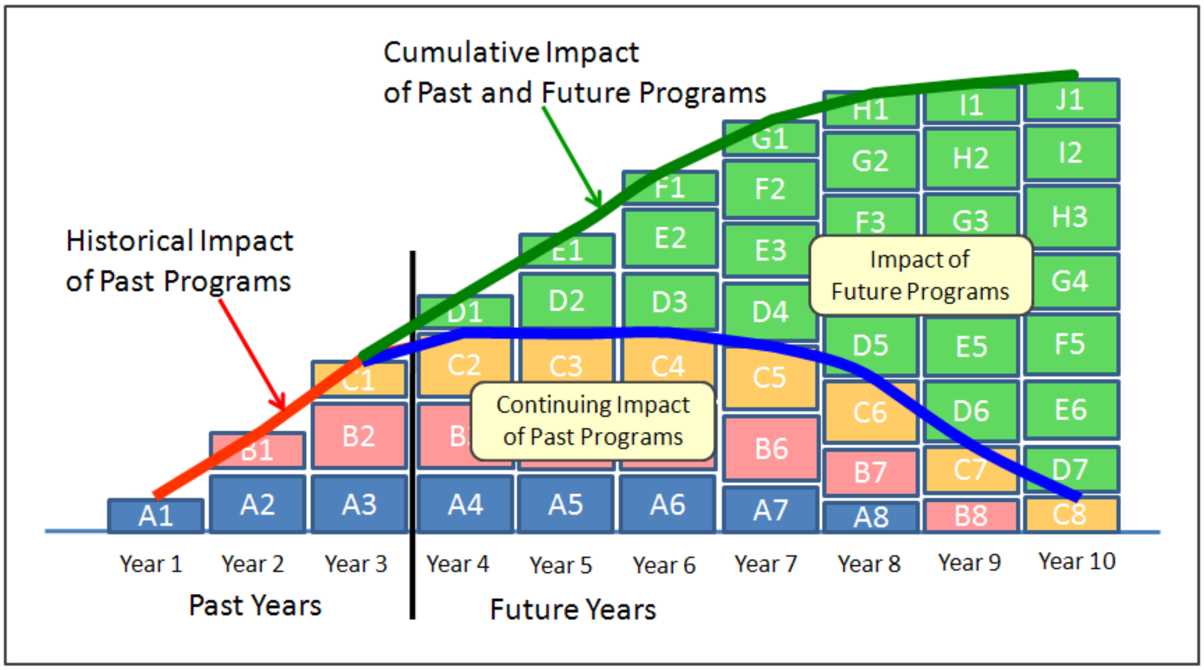


Figure 2 illustrates the key timing issues associated with DSM impact accounting. In the example, programs are run in each of the three historical years. The total energy impact from the historical program activity is represented by the red line. If there are no further programs in years 4 and beyond, then the blue line represents the continuing cumulative impact of past programs. The decline in the blue line shown in Figure 2 is attributed to the end of the measure life.

Figure 3 provides an extension to include estimates of the expected impacts of future as well as past programs. Future programs are shown as green boxes and are labeled based on the program year (D to J). The cumulative impacts of past and future programs are represented by the solid green line at the top of the impact stack for each year. Because the new program impacts are relatively stable each year, the green line eventually bends over as the decay in impacts from program years A, B, and C offsets some of the gains from the future program efforts.

Figure 3: Illustration of Impact Accounting with Future Programs



Issues for Calculation of Program Impacts

The program impact data needed by the forecaster should represent both the historical impact of past programs and the cumulative impact of past and future programs. Generally, historical savings estimates are derived from program evaluations and future program estimates are obtained from program assessments. In both cases, underlying assumptions may vary and conflict with forecast assumptions. The key issues that should be addressed when developing the impact streams are as follows.

- ***Weather:*** Many DSM programs seek to reduce energy consumption related to heating and cooling impacts. In program assessments, impacts are often estimated under the assumption of normal weather conditions. Program evaluations generally reflect patterns based on actual weather conditions. To be consistent with the statistical modeling process used in forecasting, the historical impact of past programs estimates needs to reflect the weather pattern that actually occurred and future impacts should reflect the same weather patterns used in the load forecasting process. This consistency will ensure that DSM savings associated with heating and cooling are consistent with the weather pattern that will be used in the load forecast.

- ***Realization Rates***: During the program assessment, initial estimates of DSM savings are made based on assumptions about technology adoption levels and the associated energy impacts. After the program is implemented, evaluation studies will show that actual savings will differ from the planning estimates based on the actual participation levels, estimated free rider rates, and the estimated energy usage impacts. The difference between the planning estimates and final evaluation results of program impacts reflect the estimated realization rates. Both the historical impact of past programs and the cumulative impact of past and future programs should be consistent and reflect the realized savings from DSM programs.

- ***Reference Efficiency Levels***: DSM program savings are generally calculated relative to the naturally occurring efficiency level, which reflects both energy efficiency standards and adoption of above-standard technologies based on market forces. Over time, the reference efficiency level will change because of changes in efficiency standards and changes in market conditions. These changes are reflected in the SAE efficiency trends. To be consistent with the underlying modeling process, both the historical impact of past programs and the cumulative impact of past and future programs should be measured relative to these dynamic reference levels (efficiency levels that would have occurred in absence of the programs).

- ***Technology Life Cycle***: DSM programs often include the installation of technologies that persists for multiple years. Equipment related measures have lives related to the equipment life cycle. Some measures have very long lives, such as increased insulation levels in new construction. Other measures and devices may have relatively short lives, such as efficient general service lamps, and these may be affected by measure retention rates as well as measure life times. During the historical and forecast period, both the historical impact of past programs and the cumulative impact of past and future programs should reflect the lifecycle and retention rates for the corresponding technologies. In the forecast period, the direct savings expected from past programs should decay with time based on these factors when not accounting for market transformation credits.

- ***Market Transformation***: DSM analysis sometimes calculates benefits for a program that exceed the underlying technology lifecycle. The analysis assumes that the program transforms the market or participant behavior, leading to subsequent adoption or replacement outside of the program. In Figure 2, no recognition of market transformation has been included. If DSM impacts include significant market transformation effects, extra care must be taken to insure that this does not lead to double counting of trend effects already included in SAE models.

Regardless of the modeling method that is used, it is important that DSM accounting be performed on a regular and consistent basis. The goal is to create for each program year the stream of expected impacts relative to what would have happened without the program.

Model Approaches

Once the historic DSM series has been developed, three potential econometric frameworks may be applied to account for DSM in the forecast period. The methods are designed to adjust the load forecast by accounting for the amount and the continuing momentum of the historic DSM contained in the load forecast model.

Method 1: Add Back

In this method, historic loads are reconstituted by adding into the load history the historical impact of past programs[1]. The reconstituted loads are shown in equation (1). These loads represent what energy consumption would have been had there never been any utility specific DSM programs. The reconstituted loads are used as the left-hand variable to estimate the "NoDSM" forecast model (equation 2) and generate the forecast in absence of DSM (equation 3). The final forecast of energy use is given by the "NoDSM" model forecast reduced by the forecasted cumulative impact of past and future programs (equation 4).

1 For the historical reconstitution of loads, the historical impacts of past programs are used from Figure 2. In the forecast period, the forecast (equation 4) is adjusted by the historical and continuing impacts of past programs shown in Figure 3. All values are cumulative.

$$\text{Load}_t^{\text{NoDsm}} = \text{Load}_t^{\text{Measured}} + \text{DSM}_t^{\text{PastPgms}} \tag{1}$$

$$\text{Load}_t^{\text{NoDsm}} = F(\text{Econ}_t, \text{Wthr}_t, \ldots) + e_t \tag{2}$$

$$\text{Fcst}_t^{\text{NoDsm}} = F(\text{Econ}_t^{\text{Fcst}}, \text{Wthr}_t^{\text{Norm}}, \ldots) \tag{3}$$

$$\text{Fcst}_t = \text{Fcst}_t^{\text{NoDSM}} - \text{DSM}_t^{\text{PastPgms}} - \text{DSM}_t^{\text{FuturePgms}} \tag{4}$$

where

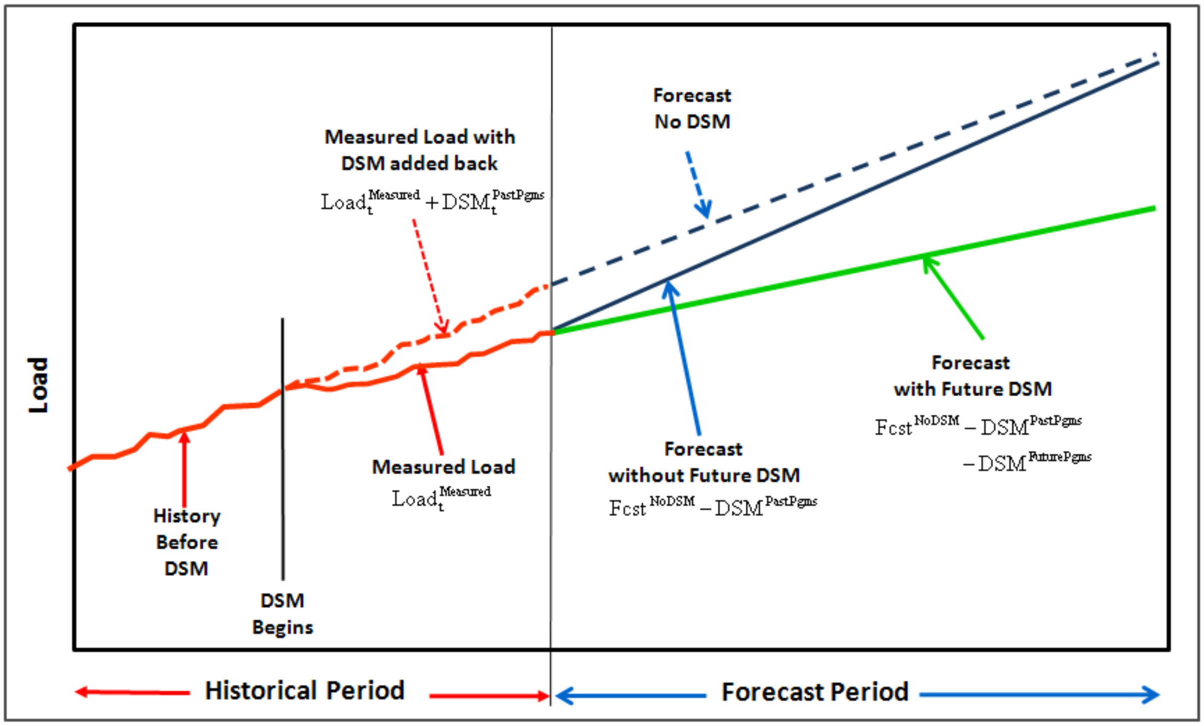
F(…)	=	Forecasting model (e.g. regression model) with residual values (e)
Econ	=	Economic historical data
$\text{Econ}^{\text{Fcst}}$	=	Economic variable forecast
Wthr	=	Actual historical weather data
$\text{Wthr}^{\text{Norm}}$	=	Normal weather scenario
$\text{DSM}^{\text{PastPgms}}$	=	Cumulative historical and continuing impact of past programs[1]
$\text{DSM}^{\text{FuturePgms}}$	=	Cumulative impact of future programs[2]

The estimate of DSM impacts from past programs ($\text{DSM}^{\text{PastPgms}}$) in the forecast period represents the continuing impact of past programs and reflects the measure life of actions caused by these programs over forecast horizon. These impacts are shown as the blue line in Figures 2 and 3. The forecast of the impacts of future programs ($\text{DSM}^{\text{FuturePgms}}$) is the expected savings from new programs or renewal of existing programs in the forecast horizon. These impacts are shown as the green boxes in Figure 3. The combination of the two impacts (past and future) is represented by the green line in Figure 3.

Figure 4 illustrates the forecast method. In this figure, the solid red line illustrates historical measured loads ($\text{Load}^{\text{Measured}}$). The dashed red line represents the reconstituted loads with historical DSM impacts added ($\text{Load}^{\text{Measured}} + \text{DSM}^{\text{PastPgms}}$). The model is developed using the reconstituted loads as the left-hand variable (equation 2). This equation represents an estimate of what would have happened without DSM programs. The model generates the forecast of reconstituted load ($\text{Fcst}^{\text{NoDSM}}$) and is shown by the dashed blue line (equation 3). The dashed blue line is then adjusted downward to account for the continuing impacts of past DSM program ($\text{DSM}^{\text{PastPgms}}$) and the impacts of future DSM programs ($\text{DSM}^{\text{FuturePgms}}$). The final forecast is shown as the green line (equation 4).

2 The forecast (equation 4) is reduced by the cumulative impacts of future programs shown in Figure 3 by the green boxes.

Figure 4: Method 1 Illustration



Key Issues

The strength of this method is that it explicitly accounts for historical and forecasted DSM at the utility level. However, this strength exposes the primary issue, which is the reliance on accurate and consistent estimates of cumulative program impacts in the past and every year in the future.

- ***DSM Data Accuracy.*** Because the historic DSM savings estimates are used to reconstitute load, the accuracy of these estimates has a significant impact on the econometric model parameters and forecast. It is important that the estimated program impacts are conceptually correct and contain consistent assumptions around the natural efficiency gains contained in the econometric model.

- ***National DSM Assumption***. In the SAE model framework, the reconstitution of loads does not make any adjustments for the national level DSM that is included in the energy efficiency trends. As such, the SAE framework still assumes that national energy efficiency trends continue at a steady pace. To estimate the NoDSM model ($\text{Fcst}^{\text{NoDSM}}$) without national level DSM, it would be necessary to estimate what efficiency trend values would have been throughout history without any DSM programs and to forecast what they would be without further programs. This is an awkward task because the default (EIA) data include DSM program impacts and there are no readily available estimates without these impacts.

Method 2: DSM Variable

In this method, an exogenous DSM variable is included as a right-hand variable in the SAE model. The generalized equation is shown in (5). In this equation, the DSM variable represents the cumulative historical impact of past programs.3 Also, on the right-hand side are the SAE variables.

$$\mathrm{Load}_t^{\mathrm{Measured}} = F\left(\mathrm{DSM}_t^{\mathrm{PastPgms}},\ \mathrm{XHeat}_t, \mathrm{XCool}_t, \mathrm{XOther}_t\right) + e_t \qquad (5)$$

where

$F(\ldots)$	=	Forecasting model (e.g. regression model) with residual values (e)
XHeat_t	=	SAE Heating variable
XCool_t	=	SAE Cooling variable
XOther_t	=	SAE Other variable
$\mathrm{DSM}_t^{\mathrm{PastPgms}}$	=	Cumulative impact of past programs

Once the model is estimated, it can be used to generate a forecast without future programs by setting the forecast values for the DSM variable to equal the cumulative continuing impact of past programs[4].

$$\mathrm{Fcst}_t^{\mathrm{NoFuturePgms}} = F\left(\mathrm{DSM}_t^{\mathrm{PastPgms}},\ \mathrm{XHeat}_t^{\mathrm{Fcst}},\ \mathrm{XCool}_t^{\mathrm{Fcst}}, \mathrm{XOther}_t^{\mathrm{Fcst}}\right) \qquad (6)$$

where

$\mathrm{XHeat}_t^{\mathrm{Fcst}}$	=	SAE Heating variable
$\mathrm{XCool}_t^{\mathrm{Fcst}}$	=	SAE Cooling variable
$\mathrm{XOther}_t^{\mathrm{Fcst}}$	=	SAE Other variable
$\mathrm{DSM}_t^{\mathrm{PastPgms}}$	=	Cumulative historical and continuing impact of past programs

The model can also be used to generate a forecast with future programs by setting the forecast values for the DSM variable to equal the cumulative impacts of past and future programs[5].

$$\mathrm{Fcst}_t^{\mathrm{WithFuturePgms}} = F\left(\mathrm{DSM}_t^{\mathrm{PastPgms}} + \mathrm{DSM}_t^{\mathrm{FuturePgms}},\ \mathrm{XHeat}_t^{\mathrm{Fcst}},\ \mathrm{XCool}_t^{\mathrm{Fcst}}, \mathrm{XOther}_t^{\mathrm{Fcst}}\right) \qquad (7)$$

3 In this paper, the discussion assumes that the DSM variable is a kWh value as illustrated by the red line in Figure 2. However, the DSM variable may also be represented as a kW or dollars invested value.

4 The cumulative continuing impact of past programs is shown as the blue line in Figure 2 and Figure 3.

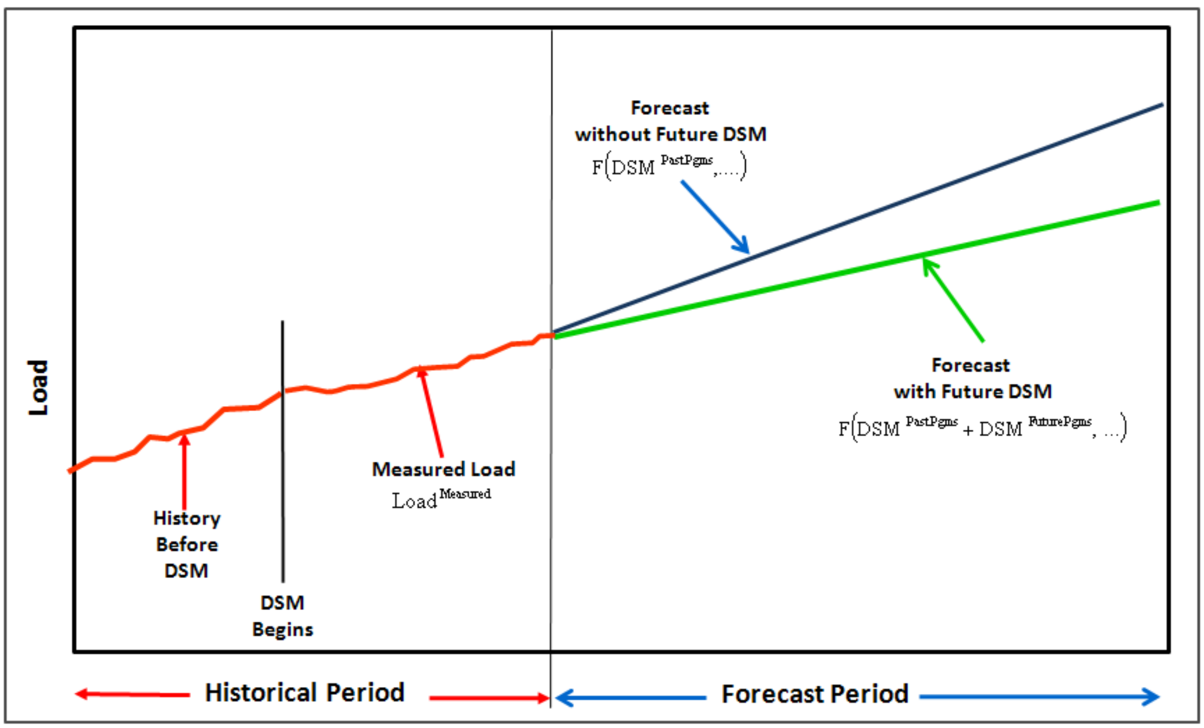
5 The cumulative impact of past and future programs is illustrated by the green line in Figure 2.

where

$XHeat_t^{Fcst}$	=	SAE Heating variable
$XCool_t^{Fcst}$	=	SAE Cooling variable
$XOther_t^{Fcst}$	=	SAE Other variable
$DSM_t^{PastPgms}$	=	Cumulative historical and continuing impact of past programs
$DSM_t^{FuturePgms}$	=	Cumulative impact of future programs

Figure 5 illustrates this method. The actual history (the red line) is used to estimate the forecast model parameters. The forecast model is then used to generate the forecast assuming only the cumulative impact of past programs, but no future DSM programs (the blue line). The forecast model is then used to generate the forecast with cumulative impacts of past and future programs (the green line).

Figure 5: Method 2 Illustration



In the estimated model, the coefficient on $DSM^{PastPgms}$, represents a statistical realization rate for the estimated DSM savings. If the estimated impacts of DSM accurately represent the savings over and above what otherwise would have occurred, then the coefficient should be close to -1.0. If the coefficient is smaller in absolute value (e.g., -.75), then the statistical model suggests that the actual realized DSM impacts are less than the program impact estimates. Ignoring the negative sign, the estimated coefficient is a statistical realization rate. By applying the estimated coefficient to the future program impacts, the modeler assumes that the realization rate for future program impacts is the same as it is estimated to be for past program impacts.

Key Issues

Like Method 1, this method requires a set of accurate and consistently defined estimates for cumulative program impacts above market standards. However, the importance of accuracy is lessened by the estimation of the statistical realization rate. If program impact estimates are overly aggressive, a statistical realization rate should be less than 1.0. If program impact estimates are overly conservative, the statistical realization rate should be greater than 1.0. It is still important that the estimated impacts of past and future programs are defined consistently over time.

- ***Statistical Significance of the DSM Coefficient***: Statistical estimation of the DSM variable coefficient requires that there have been large and significant programs with impacts that vary over time. The impacts should be larger than the statistical noise in the data and different than the national level of impacts already included in the SAE variables. There is a danger that the DSM variable will be highly correlated with other variables which may make it difficult to identify the independent impact of the DSM variable. If the utility programs have been comparable to the regional efforts, the DSM variable would have an expected coefficient of zero in the model since the regional DSM impacts are already accounted for in the SAE variables.

- ***DSM Variations***: Using a single DSM variable assumes that the aggregate of DSM programs have a common realization rate. Of course, it would be possible to include multiple DSM variables, organized by program type or end-use. However, it is unlikely that this will produce statistically meaningful results because the disaggregated impacts will likely be small and collinear.

Method 3: DSM Trend

Methods 1 and 2 make explicit efforts to adjust DSM out of the history and out of the forecast. Method 3 takes a different approach by recognizing that historical DSM and DSM trends are embedded in the actual sales data. Forecasting models that are built on these data implicitly assume that the levels and trends for DSM savings in the history continue into the forecast at approximately the same rate. As a result, the forecast only needs to be adjusted if DSM impacts are expected to be greater or less than the historical trends.

Like methods 1 and 2, this method requires cumulative DSM impact data for the historical period. Based on the historical impact of past programs, a simple trend model is implemented. For example, a simple linear model would have the form shown in equation (8)

$$\mathrm{DSM}_t^{\mathrm{PastPgms}} = b_0 + b_1 \times \mathrm{Time}_t + e_t \tag{8}$$

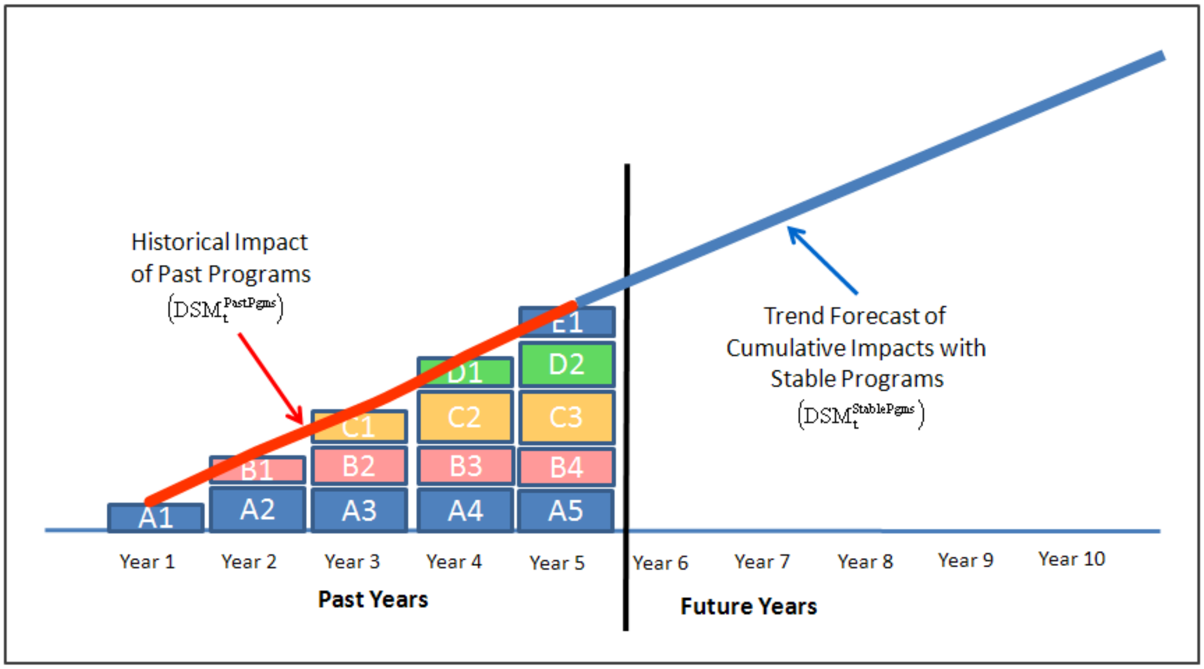
where time is the simple trend variable that increases by 1.0 each year. While equation (8) shows a simple model, the model can be more complicated using trend shifts, seasonal trends, or perhaps nonlinear trend variables. The key is that the types of trend variables used here are consistent with the types of trend variables included in the estimated energy model.

The estimated parameters of the DSM trend model (equation 8) can be used to develop a trend forecast for cumulative DSM impacts. This trend forecast (equation 9) assumes that program activity levels are stable, generating a relatively stable trend in the cumulative impact of past and future program.

$$\mathrm{DSM}_t^{\mathrm{StablePgms}} = \hat{b}_0 + \hat{b}_1 \times \mathrm{Time}_t \tag{9}$$

This idea is depicted in Figure 6. The figure drawn assumes 5 years of historical DSM activity (program years A to E), and shows a 5 year extension of the cumulative trend line corresponding to equation (9). This is the DSM trend line ($\mathrm{DSM}_t^{\mathrm{StablePgms}}$).

Figure 6: Method 3 – DSM Trend Analysis



The next step is to estimate a forecast model based on measured historical sales. This model would take the following general form:

$$Load_t^{Measured} = F(XHeat_t, XCool_t, XOther_t) + e_t \quad (10)$$

where

F(…)	=	Forecasting model (e.g. regression model) with residual values (e)
$XHeat_t$	=	SAE Heating variable
$XCool_t$	=	SAE Cooling variable
$XOther_t$	=	SAE Other variable

This is unlike equation (2) in Method 1 because the left hand variable has not been adjusted upward for DSM impacts. It is also unlike equation (5) in Method 2 because there is no DSM variable in the model. Once the model is estimated (10), it can be used to generate a forecast of energy use assuming continuation of DSM program impact trends as shown in equation (11).

$$Fcst_t^{StablePgms} = F\left(XHeat_t^{Fcst}, XCool_t^{Fcst}, XOther_t^{Fcst}\right) \quad (11)$$

where

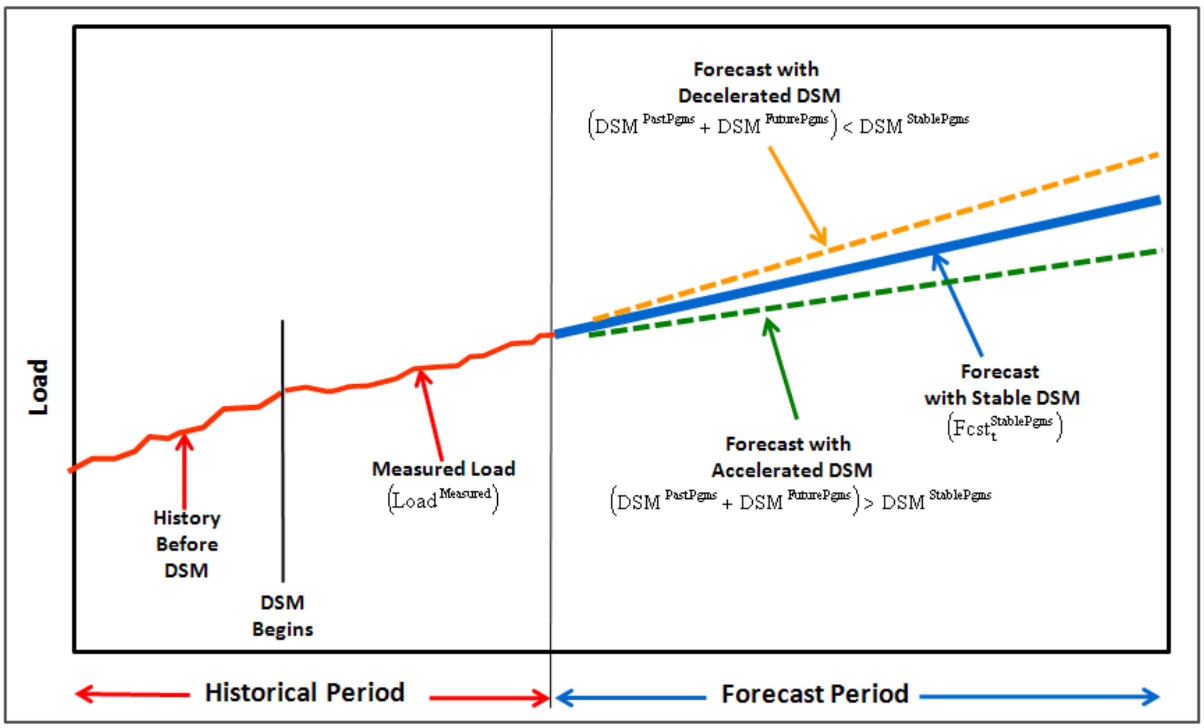
$XHeat_t^{Fcst}$ = SAE Heating variable

$XCool_t^{Fcst}$ = SAE Cooling variable

$XOther_t^{Fcst}$ = SAE Other variable

The idea behind Method 3 is shown in Figure 7. The historical model is estimated with measured load data, as represented by the solid red line. The forecast is represented by the solid blue line ($Fcst^{StablePgms}$). Because cumulative DSM impacts and their trends are embodied in the historical data, the projection of these data implicitly assumes that the trends in the DSM impacts will extend into the forecast period. In other words, the forecast (blue line in Figure 7) implicitly includes the DSM trend line ($DSM^{StablePgms}$) developed in equation (9).

Figure 7: Method 3 – Forecasts and Acceleration Adjustments



In the final step of Method 3, the forecast is adjusted if the cumulative impacts of past and future programs are expected to accelerate or decelerate relative to the DSM trend line ($DSM^{StablePgms}$). For example, if the DSM trend line forecast is forecasting 100 MWh in a future year and the cumulative impact of past and future programs are expected to be 120 MWh in the same future year, the forecast should be adjusted downward 20 MWh. In this method, the forecast is adjusted up or down by the difference between the DSM trend line and the cumulative impact of past and future programs.

If the total cumulative impact of past and future programs is expected to fall short of the historical trend, then the energy forecast should be adjusted upward by the amount of the deceleration below the DSM trend line. This adjustment is represented by the following final energy forecast equation (12).

$$\begin{aligned}\text{Fcst}_t &= \text{Fcst}_t^{\text{StableDSM}} + \text{DSMAcceleration}_t \\ &= \text{Fcst}_t^{\text{StableDSM}} + \left(\text{DSM}_t^{\text{PastPgms}} + \text{DSM}_t^{\text{FuturePgms}} - \text{DSM}_t^{\text{StablePgms}}\right)\end{aligned} \qquad (12)$$

This equation starts with the model forecast from equation (11) and adds in the estimated program acceleration (positive or negative) relative to trend.

If program plans call for continued steady program efforts through time, Method 3 is a convenient approach. In this case, DSM acceleration is expected to be zero, and the forecast from equation (11) is the final energy forecast.

Key Issues

This method requires the same historical DSM impact data as Methods 1 and 2. However, like Method 2, the accuracy of these estimates is reduced due to the resulting modeling of the DSM trend. Nevertheless, it is still necessary to understand the historical impact of past DSM programs. In Method 3, these data are used to develop the DSM cumulative impact projection (as shown in Figure 6). Issues with this method are as follows.

- ***Misses Lifecycle Effects***: Using the trend model, the assumption is that cumulative DSM savings grow linearly over time (assuming a linear trend model is used). This is often not the case since the the focus of DSM programs changes over time and since different technologies have different measure lives. Explicit impact accounting will more accurately represent the duration of past and future impacts as they enter the stream of cumulative impacts. In addition, long-run linear growth requires program acceleration to insure that new impacts from future programs counteract the drop off of decaying impacts from older programs.

- ***DSM Growth Trend Complexities***: As shown in equations (8) and (9), the trend model has a single coefficient on time resulting in linear growth of cumulative DSM impacts through the forecast period. This assumption may be valid if DSM efforts are expected to be relatively stable or gradually increase through time. However, programs are generally ramped up and down through time as end-use technologies, efficiency standards, and market conditions change. Further, the annual profiles of DSM impacts will be different for major end-use groupings such as heating, cooling, and lighting. Considering the complexity of DSM program implementations, equations (8) and (9) may need to be modified to reflect these effects. These differences will be important for monthly sales forecasting and peak load forecasting.

- ***DSM Trend Assumption***: The DSM trend line is a statistical attempt to capture the underlying trend in the SAE model. To the extent that the SAE model contains binary shift variables or end-shift variables, the DSM trend line may not realistically represent embedded DSM in the SAE model.

Conclusions

When using an econometric or SAE model, historical DSM investments influence the historical sales data, the forecast model parameters, and the resulting sales projections. As DSM investment increases, forecasters need to adjust their sales forecasts to account for this acceleration relative to the historic DSM that is implicitly included in an unadjusted forecast.

We have considered three methods for recognizing past DSM and adjusting the forecast for future DSM. In all methods, the forecaster initially needs to develop the cumulative impacts from past and future DSM program (Figures 1 and 2). Once the DSM data series are developed, the forecaster may explore the benefits of each method.

Method 1, "Add Back" Method

Method 1 attempts to reconstitute load by adjusting the left-hand-side of the SAE model to create a model without DSM. Once the model is developed, the forecast is adjusted to account for past and future DSM impacts. This method appears to work well in situations were there is a short history of minor DSM investments, and the historical impacts can be reconstituted from program data.

Method 2, "DSM Variable" Method

Method 2 attempts to model DSM by inserting a variable on the right-hand-side of the SAE model. Once the model is developed, the forecast is created by inserting a forecast of the cumulative impact of past and future programs. This method requires that historical programs have had a major impact on historical sales and that there is enough independent variation in the impact history to generate statistically significant parameters.

Method 3, "DSM Trend" Method

Method 3 attempts to capture the underlying DSM trend without adjusting either the right or left-hand-side of the SAE model. Assuming that the DSM trend is obtainable, the forecast is adjusted for net changes from the DSM trend line. This method is well suited to a situation where there has been a longstanding and relatively stable DSM history and where there is expected to be significant acceleration of deceleration of program activity.

Because each utility situation is unique, the methods should be explored and selected based on the availability of data and the forecaster's objectives.

Glossary

In this paper, key DSM terms are used to articulate the development of data for use in the forecasting methods. These terms are used consistently throughout the paper and do not represent formal definitions used throughout the electric industry.

Cumulative Impact

In this paper, the **cumulative impact** in a year means the DSM savings that occur in that year resulting from programs in that year and all past years. In Figure 2, the cumulative impact is shown as the vertical sum of a column. For example, in Year 3, the cumulative impact of Programs A, B, and C is represented by the blocks labeled A3 + B2 + C1. Cumulative impacts may apply to the historical impacts of past programs, the continuing impact of past programs, and the impact of future programs.

Historical Impact of Past Programs

The **historical impact of past programs** is the realized DSM savings from implemented programs in past years. In Figure 2, the historical impacts are shown in blocks A1 through A3, B1 through B2, and C1. These impacts may also be shown as cumulative impacts. The cumulative impacts associated with these programs are shown by the red line in Figure 2.

Continuing Impact of Past Programs

The **continuing impact of past programs** is the future DSM savings expected from programs that were implemented in past years. In Figure 2, program A begins in Year 1. The savings from this program will continue throughout the measured live of the DSM technology. While Years 1 through 3 represent historical years, Year 4 represents the beginning of the future. The continuing impact of program A is the expected DSM savings beginning in Year 4 and is represented by blocks A4 through A8. These impacts may be cumulative when added with the expected savings of other program (B and C) that have been implemented in the past.

Cumulative Impact of Future Programs

The **cumulative impact of future programs** are the future DSM savings expected from future programs. In Figure 3, future programs begin in Year 4 and are represented by the green squares. The cumulative impact of future programs is the vertical sum of the green squares in a single year. For example, in Figure 3, Year 6, the cumulative impact of future programs is D3+E2+F1. These impacts exclude credits for market transformation.

Cumulative impacts past and future DSM programs

The **cumulative impact of past and future programs** are the DSM savings across both historical and future programs measured in a single year. In Figure 3, this impact is represented by the solid green line at the top of the impact stack in each year. In this paper, these impacts generally exclude credits for market transformation.

Itron Inc.

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