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Modeling an aggressive energy-efficiency scenario in long-range load forecasting for electric power transmission planning

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HIGHLIGHTS

- Improved representation of end-use energy efficiency is needed for load forecasting.
- An emergent application is long-range electric power transmission planning.
- A "hybrid" econometric-technology forecasting approach incorporates efficiency.
- A high efficiency scenario was created for Western U.S. transmission planning.
- Significant load-growth reductions from increased end-use efficiency are possible.

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ABSTRACT

Improving the representation of end-use energy efficiency, and of the effects of policies and programs to promote it, is an emergent priority for electricity load forecasting models and methods. This paper describes a "hybrid" load forecasting approach combining econometric and technological elements that is designed to meet this need, in a novel application to long-run electric power transmission planning in the western United States. A twenty-year load forecast incorporating significant increases in energy-efficiency programs and policies across multiple locations was developed in order to assess the potential of efficiency to reduce load growth and requirements for expanded transmission capacity. Load forecasting and transmission planning background is summarized, the theoretical and empirical aspects of the hybrid methodology described, and the assumptions, structure, data development, and results of the aggressive efficiency scenario are presented. The analysis shows that substantial electricity savings are possible in this scenario in most residential and commercial end-uses, and in the industrial sector, with magnitudes depending upon the specific end-use as well as upon the geographic location of the utility or other entity providing the electricity.

1. Introduction

Analyzing and projecting consumers' and firms' consumption of electricity is one of the core applications of computational energy modeling. Over the past several decades, various methods for this problem of "load forecasting" have been applied by electric utilities, energy policy-makers, and other decision-making entities in the electric power system. Recently, new technological and policy developments related to electric power production, transmission, and consumption have placed new demands upon load forecasting methodologies. Expanded features including increasing levels of detail, longer time horizons, and the capacity to address an expanded set of policy and regulatory requirements, are being required in load forecasting models' range of functionality.

Improving the representation of end-use energy efficiency, and of the effects of policies and programs to promote it, are among the priorities for enhancing load forecasting models and methods. Efficiency has become an important element of many utilities' resource mix for meeting the demand for electrical energy services, as well as a key component of numerous policy portfolios for large-scale abatement of carbon dioxide emissions from the electric power system. Such developments necessitate new approaches, and extensions of existing approaches, to load forecasting.

This paper describes such an approach in application to an important example of emerging problems in load forecasting:

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Nomenclature

AEO Annual Energy Outlook – U.S. national energy forecast, produced by EIA using NEMS
BA balancing authority – electric power control and planning area
CHP combined heat and power
COP coefficient of performance – metric of heating or cooling output per input of electric energy; an index of energy efficiency
Diversity factor ratio of coincident peak demand for a BA (BA load at time of WECC system-wide peak)to non-coincident peak (actual BA peak value)
DSM demand-side management – programs (usually by electric utilities) to reduce or change end-use energy and/or peak demand, including through promoting end-use efficiency
EER energy efficiency ratio – for a cooling device, ratio of cooling output in btu to electrical input in watt-hours at a given operating point
EIA Energy Information Administration – U.S. national energy statistical and analytical agency, within the U.S. Department of Energy (but reporting to the U.S. Congress)
EMMA environmental and emission model for Adam – Danish energy model
HSPF heating seasonal performance factor – ratio of heating output in btu to electric energy consumed to produce it, both over a season; a metric of energy efficiency
HVAC heating, ventilation, and cooling
LSE load-serving entity – a company or organization providing electricity services to retail or wholesale customers
NEMS National Energy Modeling System – U.S. national energy forecasting model, maintained and used by EIA
SAE statistically-adjusted end-use – load forecasting methodology combining econometric and technology end-use elements and techniques
SEER seasonal energy efficiency ratio – For a cooling device, ratio of cooling output over a season to electrical input over the same period
UEC unit energy consumption – metric of energy efficiency for certain types of devices; typically in kW h per year
WECC Western Electricity Coordinating Council – electric power transmission planning and operations organization in the Western U.S
WI Western interconnect – component or grid of the North American electric power system, serving the Western U.S. and Canada and Northern Mexico

Incorporating energy efficiency into long-run electricity transmission planning. The approach is a "hybrid" load forecasting and modeling framework combining econometric and technological elements, focusing on a higher level of aggregation than is commonly incorporated in standard efficiency potential studies, while still allowing for the representation of end-use technology detail.

Transmission planning itself is undergoing significant changes to meet new policy priorities and regulatory constraints, including the expanded deployment of renewable energy sources and increased requirements for system reliability. The analysis discussed here was undertaken in support of a multi-institution, multi-stakeholder initiative to improve transmission planning in the Western Electricity Coordinating Council (WECC), a federally-sanctioned transmission operations and planning organization. Projections of future load growth across the WECC and scenarios of expanded energy efficiency programs and policies were created in order to examine the implications of increased efficiency for the development of the transmission system. The purpose was to enable subsequent analysis, using transmission planning modeling, of how greater end-use efficiency, by reducing load growth, might affect requirements for future transmission capacity expansion. In this paper we describe the design and implementation of a scenario of aggressive efficiency or high "demand-side management (DSM)" programs, policies, and regulations that would significantly increase the deployment of efficient end-use technologies across the WECC and therefore substantially reduce load relative to the projected baseline.[1]

The paper is organized as follows. In the next section, we provide background on load forecasting, transmission planning and the WECC, and the genesis of the load forecast and aggressive efficiency scenario. Following this is a summary of the SAE framework and methodology, basic data inputs for this analysis, the representation of DSM impacts within the hybrid load forecasting framework, the treatment of uncertainty and model sensitivity, and a comparison to other approaches. Section 4 then presents the core content of the paper: the assumptions, structure, inputs, and results of the High DSM scenario. The paper ends with a discussion and concluding remarks.

2. Background

2.1. Energy efficiency and methods of load forecasting

Load forecasting methods in general have been the subject of a number of relatively recent surveys, including [2–5]. In this section we focus specifically on the issue of energy efficiency in the load forecasting context, and in Section 3.5 further discuss forecasting approaches.

Utilities increasingly treat efficiency as a resource analogous to conventional power generation, and are changing generation investment plans based on anticipated efficiency acquisitions. Indeed, DSM programs and other efficiency policies are among the causes of steadily slowing electricity sales growth in recent decades [6]. The expanding implementation of these programs is stimulating changes to forecasting procedures.

Traditionally, one or more of three methods have been used for electric utility load forecasting: (i) Extrapolation of past trends; (ii) Econometric modeling; (iii) Technologically-detailed end-use energy modeling [7]. Each method remains in use, although the econometric approach has come to predominate. In this approach, load is predicted as a function – typically linear – of inputs including weather (usually heating and cooling degree days), demographic and income (for residential) or building stock (often square-footage, for commercial) variables, and prices, plus an error term. The time-unit of analysis can be hourly, monthly, or annual. Parameters are estimated on historical data.

Regarding end-use energy efficiency, this approach captures the future, ongoing effects of utility DSM, and policies such as building or appliance minimum-efficiency standards, that are reflected in historical data. At the utility level, however, some adjustment of load forecasts is needed to account for additional impacts that might result from expanded or additional future programs. The

[1] Additional detail on the work described in this paper is contained in a longer technical report [1]. Demand-side management includes energy efficiency as well as load management by end users.

most common adjustments are exogenous, *ex post* reductions to the econometric forecasts [8]. However, this technique is limited in its capacity to capture the details of efficiency programs and their load impacts because, among other reasons, end-use information that might be used for such adjustments is not easily integrated into a statistically-based forecast.

Conversely, technologically detailed end-use forecasting – by utilities or other entities – can explicitly account for end-use efficiency characteristics of both equipment and buildings. This methodology is usually based upon a stock-accounting framework, in which the electricity consumption is "built up" from equipment and building stock information, device-specific technical efficiencies, and – as in the econometric approach – factors such as prices, demographics, income, and building sizes. In this case, however, the representation is strictly deterministic – traditionally, no error terms appear in a model of this type, nor are statistical estimation procedures used to determine values of parameters, which are obtained from other sources. In lieu of a statistical "fit" to historical empirical data, such models are informally calibrated to, for example, trends in such data, benchmark years, or both. In contrast to the econometric approach, this type of end-use modeling is well-suited to capture the details of energy efficiency. However, its deterministic foundation precludes rigorous, quantitative treatment of important uncertainties that affect loads.

A noteworthy example of this methodology is the demand modeling and forecasting system of the California Energy Commission [9]. This system was originally developed in the 1970s and has been maintained and updated since, and has become a central analytical tool for California energy policy. Among its most important current applications is its use to create 10-year forecasts (with annual time steps) that the state's investor-owned utilities are required to use in conjunction with their own forecasts for purposes including energy efficiency planning. At a larger scale, the residential and commercial modules of the U.S. Energy Information Administration's (EIA) National Energy Modeling System (NEMS) are also based in large part upon stock accounting principles [10]. EIA is part of the federal Department of Energy, and among the uses of NEMS is production of the *Annual Energy Outlook (AEO)*, a two-decade (with annual time steps) multi-sector, multi-fuel national energy forecast [11].[2]

The relative advantages and limitations of econometric and detailed end-use modeling with respect to representing and analyzing DSM and other efficiency policies and programs in load forecasts, and the increasing need for such functionality, indicate the potential usefulness of so-called "hybrid" forecasting methods, which combine statistical modeling with end-use technology detail. The load-forecasting methodology discussed in this paper is an example, called the "statistically-adjusted end-use (SAE)" approach. It was developed by Itron, Inc. to extend the standard utility econometric load forecasting methodologies in order to incorporate information on DSM and other efficiency measures, to account for the effects of these programs on loads, including the potential effects of new or changed programs. Previous applications of this SAE tool have included modeling the effects of federal policies and regulations – such as those for energy-efficient lighting – at the utility service territory level, and multi-utility, multi-jurisdictional, long-run forecasting of hourly loads as well as peak demands.

2.2. Transmission planning context

The Western Interconnection (WI), serving the western US and Canada, and northern Mexico, is one of three large-scale components or "grids" comprising the North America bulk power transmission system.[3] Operations within the WI and other grids are divided among a set of "balancing authority areas" (or "control areas"), which are geographical areas in which generation, transmission, and loads within metered boundaries are integrated by a single entity – a balancing authority (BA) – which also maintains the area's load-resource balance, and supports the area's interconnection frequency in real time. The WI is the purview of WECC, one of eight regional entities across the continent authorized by the federal government to maintain and improve reliability of the bulk-power system, with activities including regional electricity transmission analysis, modeling, and planning. WECC membership includes the thirty-seven BAs in the WI, which encompasses all or parts of fourteen US states on the Pacific coast, the Rocky Mountain and Southwest regions, the Canadian provinces of Alberta and British Columbia, and the northern part of Baja California in Mexico (see Fig. 1).

The analysis described in this paper was conducted as part of WECC's "Regional Transmission Expansion Project" (RTEP), funded by the U.S. Department of Energy to improve transmission planning processes and outcomes in the WI, including the introduction of planning on an Interconnection-wide rather than single-utility or BA basis. RTEP entails the development of transmission plans under both 10- and 20-year planning horizons to identify future transmission expansion needs and options for meeting those needs. It has engaged a range of stakeholder groups – including state regulators and policy-makers, energy agencies, and non-profit organizations – that propose "study cases" (i.e., scenarios) that WECC evaluates using transmission planning (production cost and capacity expansion) modeling tools.

2.3. Energy efficiency scenarios

Among the RTEP study cases has been a set focusing upon energy efficiency, including utility DSM and federal appliance efficiency standards, over both 10- and 20-year planning horizons. These efficiency scenarios have been structured in terms of reference or baseline cases that incorporate future effects of current demand-side programs, policies and plans, and "High DSM" cases that represent future energy savings resulting from increased or expanded efficiency policies and programs relative to reference case assumptions. The purpose of these cases was to explore the transmission-planning implications of energy efficiency-driven reductions in future load growth.

The 10-year efficiency scenarios relied upon existing load forecasts developed by WECC BAs, and drew upon a disparate set of energy efficiency potential studies with varying methodologies and scopes. By contrast, for the 20-year analysis described in this paper, the SAE load forecasting framework and modeling tool was used to develop a new set of baseline case and High DSM case forecasts. The major advantage of the SAE methodology was to provide a common methodological framework and scope of end-use measures across all regions, and allow for more transparent and internally consistent accounting of energy efficiency impacts.

3. A hybrid modeling framework

3.1. The SAE load forecasting framework

The SAE analytic architecture is shown in Fig. 2. Historical values of various inputs (e.g., economic, weather, and building

[2] In NEMS, the industrial sector is modeled using a reduced-form econometric approach.

[3] Transmission infrastructure also includes a network of facilities at the distribution – utility and retail – level. The work discussed his paper focused solely on the bulk power system.

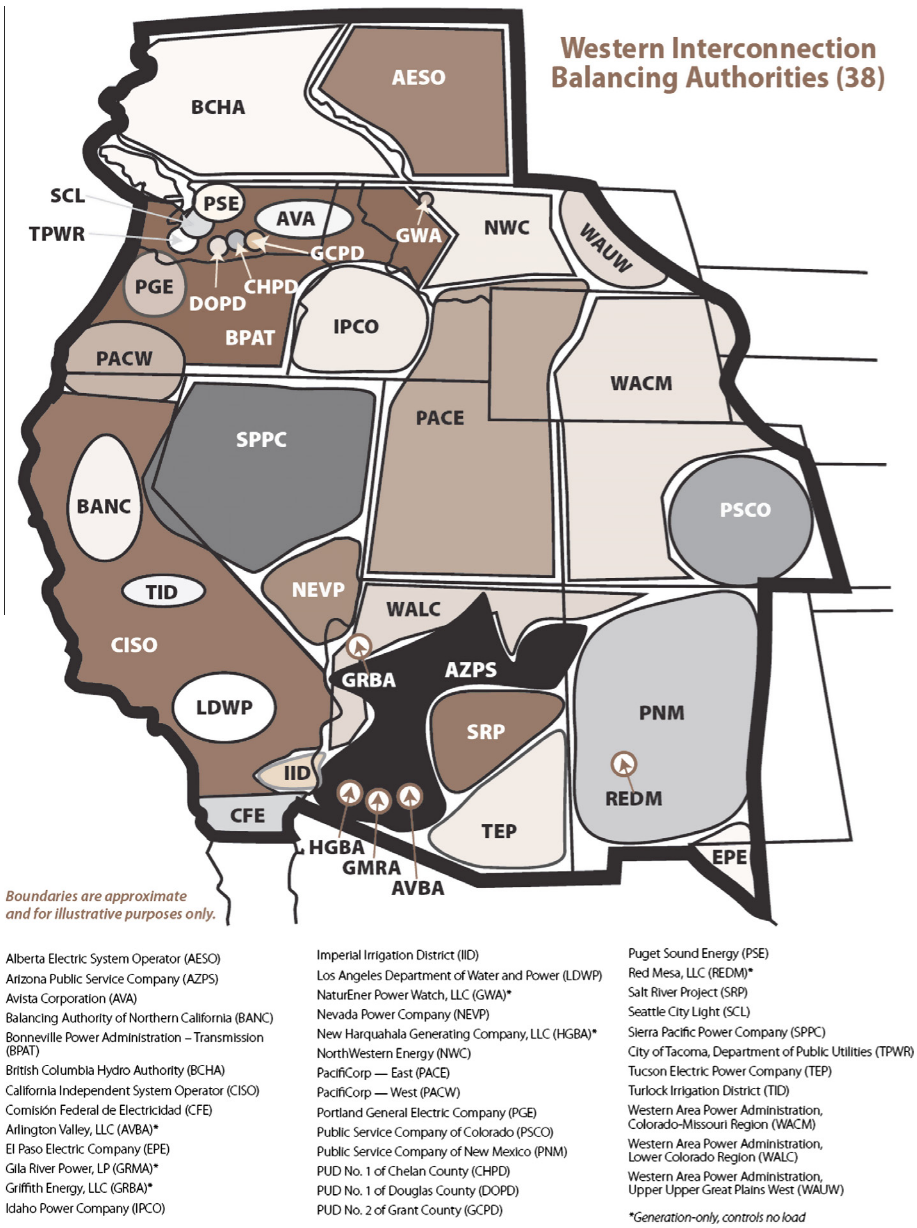

Fig. 1. Map of WECC.

stock data) are used to estimate the individual models. Forecasts of those variables are then used to drive forecasts of monthly energy and peak demand, which are disaggregated into specific end-use categories.[4]

The core of the SAE framework is a set of econometric models of the form

$$Energy_m = a + b_c XCool_m + b_h XHeat_m + b_o XOther_m + \varepsilon_m, \tag{1}$$

where monthly energy consumption (*Energy*) is represented as a function of a set of indices (*XCool*, *XHeat*, and *XOther*) constructed from detailed end-use, building stock, and other data. These inputs and their relation to the model are illustrated in Fig. 3. For the analysis discussed in this paper, models of this form were estimated for monthly energy use and monthly peak demand, for each sector (residential, commercial, and industrial) within each BA in WECC.

As Fig. 3 suggests, SAE models are data-intensive. This analysis used hourly load data for each BA, extending over the period 1998–2010. For the purpose of estimating the model, these data were transformed into monthly energy and peak loads. Economic and demographic data were obtained from an economics consulting firm (Moody's) and included both historical and forecasted data for the number of households, population, income, employment, and gross state product for each U.S. state in the Western Interconnection and for the three primary urban areas (Vancouver, Calgary, and Edmonton) within the two Canadian provinces in WECC. Historical weather data obtained from DTN (a subscription service) consisted of daily average dry bulb temperatures for 100 weather stations dispersed throughout WECC for the period 1991–2011. From those data, average weather conditions (cooling degree days, heating degree days, and peak producing weather) were computed for each BA and month, and were used as inputs for the load forecasts.

The final inputs for the SAE model are building stock and end-use data. The end-use data consist of historical data and forecasts

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[4] In this paper we discuss only projected annual energy usage in the WECC scenarios; the corresponding forecasts of peak demand are presented in [1].

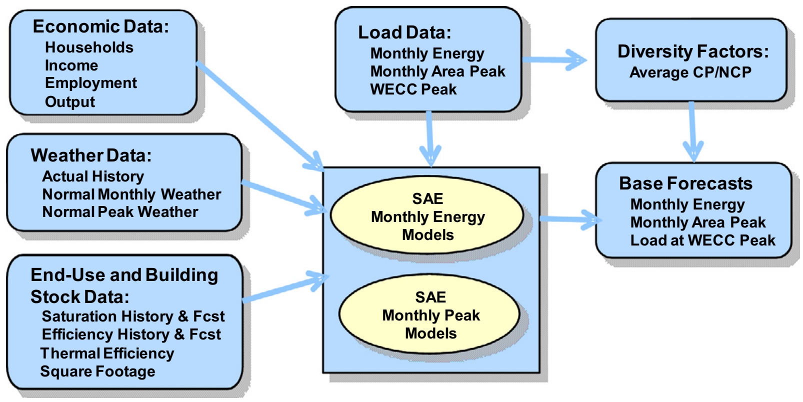


Fig. 2. SAE modeling framework. *Source*: [12]

for the saturation and average stock efficiency levels of 30 separate residential and commercial end-uses (see Table 1). The definitions of end-use categories, as well as the units used to characterize efficiency, are taken with some variations directly from those used in the EIA NEMS.

In general, the default end-use saturation and stock efficiency assumptions in SAE applications are taken from the EIA's *AEO* 2012 Reference Case [11]. These national forecasts are generated with NEMS and are disaggregated to the U.S. Census region level. We augmented these default inputs by substituting state- or utility-specific end-use data when available (see Section 4).

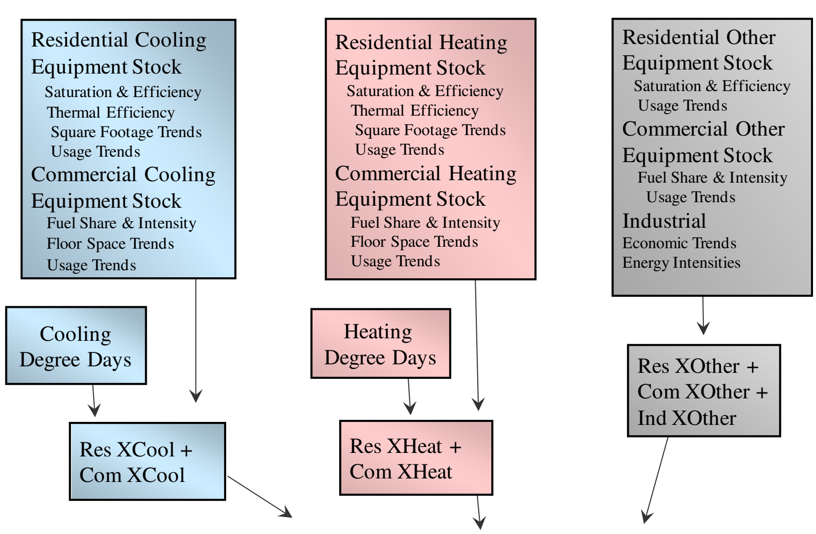
Data quality is very good for the dependent variables, monthly energy and peak load, both of which are calculated from transmission zone hourly load data. Similarly, weather data from Automated Surface Observation System (ASOS) stations are generally accepted as being highly accurate and reliable. Historical economic and demographic data at the state level are from widely-used government sources, and are believed to be reliable. End-use data quality is fairly good for most of the major residential appliances and commercial end-use categories, based on a significant historical record of end-use research, including saturation surveys, utility program evaluation studies, national surveys conducted by the EIA, and detailed end-use measurement studies conducted over the last several decades. Data quality is lowest for the miscellaneous usage category, which includes a broad array of plug-in devices, particularly electronic equipment.

Table 1
End-uses represented in SAE framework. *Source:* [14].

Residential		Commercial
Furnace	Cooking	Heating
Heat Pump	Refrigerator	Cooling
Ground source heat pump	Second refrigerator	Ventilation
Secondary heat	Freezer	Waste heat
Furnace fan	Dish washer	Cooking
Central air-conditioning	Clothes washer	Refrigeration
Heat pump cooling	Dryer	Outside lighting
Ground source heat pump cooling	Television	Inside lighting
Room air-conditioning	Lighting	Office equipment
Water heating	Miscellaneous	Miscellaneous

3.2. Accounting for energy efficiency in the SAE framework

The SAE approach is designed to facilitate the representation of end-use efficiency and the analysis of its role in electricity consumption and demand, including the effects of DSM programs



$$Energy_m = a + b_c \times XCool_m + b_h \times XHeat_m + b_o \times XOther_m + e_m$$

Fig. 3. SAE econometric framework. *Source*: [13]

and efficiency-promoting policies. Energy efficiency policy and program impacts are embedded in two ways in the SAE load forecasting methodology. First, efficiency improvements are captured in the stock efficiency data and projections used to develop the SAE end-use indices (i.e., the right-hand side in Eq. (1)). Second, when the SAE model is estimated from historical load data, the effects of historical DSM programs embedded in such data (i.e., the left-hand side of Eq. (1)) will be reflected in the resulting model.

The default stock efficiency projections of the *AEO* Reference Cases partially capture future energy efficiency program and policy impacts. EIA is required by the U.S. Congress to be "policy-neutral" and therefore, in its Reference Case projections, endeavors to incorporate the effects only of federal, state and local policies and programs that are already in place at the time of the projection, or that have been both enacted and have had any required enabling legislation and/or funding appropriations already put into effect. This approach is thus reflected in any SAE-based forecast that uses the EIA stock efficiency values. For example, these values fully capture the impact of established federal minimum efficiency standards.

By virtue of the NEMS calibration to historical load and end-use data, the *AEO* Reference Case stock efficiency projections implicitly reflect a continuation of DSM program activity at roughly the rate that has historically occurred nationally. Thus, to the extent that future DSM program activity in a specific region or utility service territory is similar to historical national trends, the use of these *AEO* stock efficiency assumptions in a localized SAE-base load forecast will capture the impact of that future DSM program activity reasonably well. However, if the expected future localized DSM program activity is, for example, more aggressive than historical national trends, then this impact will be under-estimated.

In such cases, contingent on data availability, it is necessary to develop load forecasts that reflect some higher or lower degree of DSM program intensity than what is embedded within the SAE-derived load forecast. One approach to doing so is the so-called "DSM Trend" method: the econometric model is first estimated on historical data, and therefore captures the impacts of future DSM programs at a level equal to roughly the historical national trend. Expected future increases or decreases in DSM program savings relative to the historical trend are then captured by an *ex post* adjustment. This method was used to create an SAE baseline case for WECC.[5]

The end-use detail in the SAE framework, however, in turn enables us to project future energy savings relative to this baseline resulting from efficiency increases in specific end-uses; we used this feature to create the 20-year High DSM case for WECC, as described in Section 4.

3.3. Accounting for uncertainty in the SAE framework

The SAE forecasting approach is subject to the same two types of uncertainty as any econometric forecast, model uncertainty and X (input) variable uncertainty. Model uncertainty reflects uncertainty in the estimated parameters. This can be quantified using forecast confidence intervals that are conditional on the X variable forecasts. For most of the balancing authorities in the present study, the 95% confidence interval width for the 20-year forecast is between ±4% and ±16% of the forecast value for 2032. A weighted average of the balancing authority results is slightly under 6%.

Uncertainty related to X variable forecasts is more difficult to quantify. For the SAE specification, X variable uncertainty can be divided into two components: economic drivers and end-use inputs. The economic drivers (households, employment and gross state product) determine the scale of the economy for each zone. These variables are highly correlated and energy forecasts are strongly related to these variables as a group, as shown in the sensitivity table. In some cases, the model elasticities have close to unit sum, indicating that energy usage is roughly proportional to this group of variables.

Uncertainty related to the end-use inputs is more complicated. Generally speaking, the importance of an end use is limited by the fraction of energy or peak attributable to that end use, and these fractions are reflected in the sensitivity table. For some end uses, like residential refrigerators, uncertainty is small because saturation levels are stable and because efficiency levels follow a steady path dictated by a slow stock turnover process and marginal efficiency levels driven by national standards. For others, like lighting, efficiency forecasts are based on assumptions about changes in the technology mix, in part driven by expected changes in efficiency standards. The main sources of end-use uncertainty are in the residential and commercial miscellaneous use categories, which include a large array of plug-in devices and small uses.

3.4. Model sensitivity

The SAE energy models include three broad classes of drivers: Economics, end-use saturation and efficiency values, and weather. In the end-use buildup, the residential sector inputs interact with households and utilization rates are driven by household size (population per household) and real income per household. Commercial sector inputs interact with population and nonmanufacturing employment, both of which are highly correlated with commercial square footage. Industrial sector inputs interact with manufacturing employment and real manufacturing gross state product. All economic variables are at the state level, and the relative elasticity of energy usage for each balancing authority with respect to the state-level drivers is estimated as part of the SAE process. From the estimation phase, elasticities at the mean data values are combined across balancing authorities to regional averages using forecasted shares of energy with normal weather in 2011. These results are shown in Table 2.

As the table shows, California has the strongest influence from households, population, and employment, reflecting relatively strong residential and commercial sales. The Northwest has the strongest influence from manufacturing activity, reflecting the influence of the pulp and paper industry in this region.

Sensitivities can also be examined by end use. Table 3 shows elasticities with respect to end-use groupings at the beginning of the forecast period. For all end uses, these elasticities provide an indication of the response of total energy with respect to a change in saturation or equipment density for that use. The signs can be reversed to indicate the response of total energy with respect to an improvement in average equipment efficiency. Heating and cooling sensitivities can also be thought of as the elasticity of total energy with respect to the weather drivers (multi-part heating and cooling degree variables).

As the table shows, energy elasticities with respect to cooling equipment efficiency and saturation are largest in the Southwest and smallest in the Northwest. Conversely, elasticities with respect to heating are highest in the Northwest. The industrial sector elasticities reflect are largest in the Northwest reflecting the relative strength of this sector in the Northwest region.

3.5. Comparison with other approaches

Section 2.1 summarized the aspects of econometric and technology end-use forecasting methods that motivated the SAE

[5] Other methods are described in [12].

Table 2
Model elasticities with respect to economic drivers.

Economic driver	WECC (%)	California (%)	Northwest (%)	Southwest (%)
Households and population	33.0	40.1	27.0	33.0
Household size	4.9	4.8	2.7	4.9
Income per household	2.2	2.1	1.4	2.2
Employment	40.7	43.7	42.4	40.7
Manufacturing GSP	17.5	13.8	21.7	17.5

Table 3
Model elasticities with respect to end-use drivers[a].

Residential sector	WECC (%)	California (%)	Northwest (%)	Southwest (%)
Cooling	3.7	3.8	0.9	6.7
Heating	3.0	0.9	6.0	2.4
Water heat	3.0	0.8	5.3	3.3
Refrigeration	5.0	7.3	3.3	3.7
Lighting	6.8	6.7	3.6	3.9
Appliances	4.0	4.5	2.6	2.3
Televisions	2.3	2.0	7.7	5.8
Miscellaneous	7.9	10.8	6.5	5.4
Commercial sector	WECC	California	Northwest	Southwest
Cooling	2.6	3.2	0.7	4.1
Heating	0.4	0.1	1.0	0.1
Ventilation	5.4	6.0	4.8	5.3
Water Heat	0.7	0.5	0.7	0.8
Refrigeration	4.4	5.9	3.5	3.2
Cooking	0.8	1.7	0.2	0.2
Lighting	12.7	15.1	1.9	1.4
Office equip	2.6	4.0	10.0	12.3
Miscellaneous	9.3	8.5	10.3	9.1
Industrial sector	WECC	California	Northwest	Southwest
All uses	25.6	18.1	30.9	30.0

[a] Residential cooling includes central air, room air, and heat pumps. Residential heating includes electric furnaces, heat pumps, and furnace ans. Residential refrigeration includes refrigerators and freezers. Residential appliances include cooking, dishwashers, clothes washers, and clothes dryers.

approach. The description above shows how the hybrid framework integrates the two methods to combine their respective advantages while each offsets the other's limitation. Thus, the statistical aspect overcomes the shortcomings of the usual strictly calibrationist philosophy of the end-use paradigm, while the end-use detail strengthens the pure econometric approach by allowing explicit treatment of technology detail. In particular, the hybrid methodology enables detailed treatment of energy efficiency – based upon technical and engineering characteristics – while exploiting econometric estimation of key parameters that influence efficiency's effects upon load.

It is also interesting to compare the SAE framework with the much more detailed and disaggregated energy efficiency potential methodology that is often used to project the effects of efficiency. A recent example is a comprehensive study of statewide efficiency potential conducted for the California Public Utilities Commission [15]. This study used a highly-detailed end-use model the output of which, however, was not load forecasts taking account of efficiency but rather *savings* from energy efficiency measures under various assumptions. In addition to this difference, the SAE framework is at a higher level of aggregation with respect to end-use details, and includes less detail on the specifics of building types, among other inputs – compared to this California study as well as to many other efficiency potential studies.[6] In our view, however, on the time, system, and spatial scales of the present study (twenty years, and the entire Western Interconnect across western North America), a higher level of aggregation is appropriate.

Several other examples serve to illustrate how the framework and analysis described in this paper compare to current approaches with respect to the treatment of energy efficiency. Andersen et al. [16] describe a high-resolution load-forecasting model used to project hourly-electricity consumption by location and customer characteristics in Denmark. This model uses inputs from the more aggregate "EMMA" model. The high-resolution model does not include technical efficiency information *per se*, while EMMA uses time-trends as a proxy for efficiency. Morini et al. [17] describe a methodology for optimal allocation of demand between combined heat and power (CHP), and renewable energy, systems. Their approach incorporates energy efficiency but only for CHP and HVAC equipment; nor is it directly designed for long term analysis. Yeo et al. [18] describe an urban-scale energy demand forecasting system that also includes efficiency information on building shells and HVAC only.

4. A 20-year aggressive efficiency scenario for the WECC

Using the SAE framework, we developed an initial set of base case, 20-year load forecasts for all WECC BAs reflecting regional assumptions about end-use efficiency trends based primarily upon those of EIA/NEMS. These forecasts were then adjusted by incorporating state-specific assumptions about future DSM program savings under current policies and program plans. (For convenience, we refer to both the initial and adjusted forecasts as the "SAE baseline.") Both forecasts were then used in developing the High DSM case.

[6] For the particular approach to defining an aggressive energy efficiency scenario described in the next section of this paper, the SAE also did not explicitly account for interactions among efficiency measures, which are typically addressed in highly-disaggregated potential studies. However, this caveat applies to the present study specifically, and is not a general aspect of the SAE methodology.

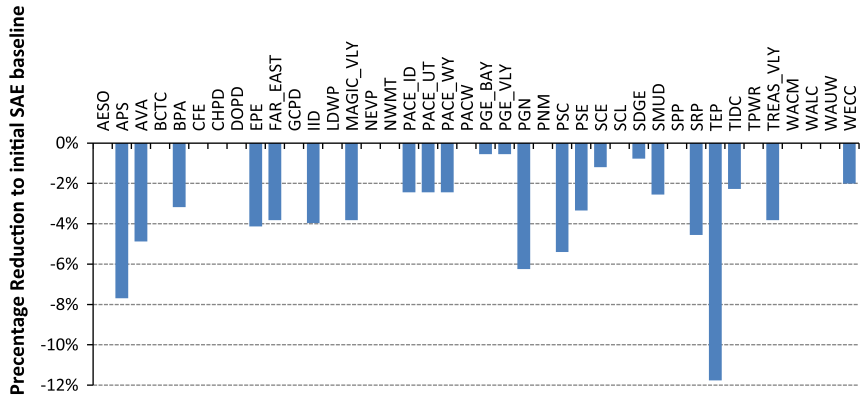


Fig. 4. SAE baseline DSM adjustments.

4.1. SAE baseline DSM adjustments

In the SAE baseline, the use of EIA stock efficiency projections for many end-uses and BAs ensures that the load forecasts will reflect a continuation of historical national average DSM program savings trends. In addition, the calibration of the model to historical load data for each BA then ensures that the load forecasts also incorporates a continuation of any historical difference between the rate of DSM savings for that BA and the national average.

The procedures for incorporating further efficiency information differed between BAs inside and outside California. For non-California BAs, we used the DSM trend method to incorporate information from the latest utility integrated resource plans from WECC BAs to take account of prospective additional future savings, relative to the BA-specific historical trend, that are anticipated from currently-planned increases in DSM program activity. The same method was used to incorporate adjustments using historical DSM savings data obtained from the EIA (Form-861, the *Annual Electric Power Industry Report*), supplemented where possible by information state PUCs or regional energy efficiency organizations.

For the California BAs, the availability of more detailed efficiency potential estimates developed for the California Public Utilities Commission [19,20], combined with the hybrid framework, allowed for the SAE baseline load forecasts to be instead developed by directly modifying the underlying end-use stock efficiency projections used to generate the load forecast, so that the expected impact of future DSM program impacts was captured via the SAE model inputs, rather than as an *ex post* adjustment using the DSM trend method.

These baseline DSM adjustments were made for 22 of the 39 load zones, where the size of the adjustment (expressed as a percentage of the SAE baseline forecast for 2032) ranged from 0% to 12% of annual energy consumption and 0–11% of annual peak demand (see Fig. 4). Again, these adjustments represent only the incremental energy efficiency savings associated with the expected "acceleration" in DSM program impacts relative to historical trends. For the remaining load zones, the expected cumulative DSM program savings under current policies and program plans was generally deemed to be similar to what would occur under a continuation of historical trends, and thus no DSM adjustments were made.[7]

4.2. High DSM case approach and assumptions

4.2.1. Overview and rationale

The High DSM study case focuses on a single year (2032), the end of the 20-year planning horizon. We stipulate average stock efficiencies for each end-use in that year and then adjust the SAE baseline load forecast for each end-use based on the efficiency improvements relative to the average stock efficiencies in the baseline for the year 2032. The average stock efficiencies stipulated for the High DSM case are intended to represent the most efficient equipment *presently* commercially available – i.e., as of 2010. That is, the High DSM Case assumes that the average stock efficiency for each end-use increases to the upper bound of technology in today's markets. This assumption was chosen based upon three criteria: (i) Aggressiveness in terms of the level of increase (thus providing a "stress test" for the transmission planning exercise); (ii) Grounding in verifiable data; (iii) Ease of communication to and understanding by a diverse stakeholder audience.

Our approach to developing the High DSM load forecasts is akin to assuming achievement of the full "technical potential" for energy efficiency, based on current commercially available technologies, in that it posits a large increase in efficiency levels relative to a baseline without addressing costs or cost-effectiveness explicitly. While we do not specify the mechanisms driving the efficiency increases in the High DSM scenario, we implicitly presume that utility DSM programs, as well as codes and standards and other potential market forces or policy interventions, may contribute.

Although presently-available "best" technologies were used to define the 2032 high-efficiency benchmarks, our approach is consistent with the emergence, commercialization, and adoption over the next two decades of even higher-efficiency units than the current best-on-market. This is because, since the focus here is on stock *averages*, the posited increases in these averages implicitly assume a corresponding increase in the high ends of efficiency ranges. Inasmuch as the current best-on-market is assumed to become the average in 2032, these high ends would be achieved with technologies that either exist currently but are not yet commercially available, are emerging, or have yet to be conceived and developed.

Our approach to creating the SAE High DSM case for residential and commercial sectors entailed the following steps

(1) For each end-use, specify the most efficient model currently commercially available.
(2) Calculate the percentage efficiency gain associated with moving from the average stock efficiency in the SAE baseline forecast for 2032 to the most efficient model currently commercially available.
(3) Apply the associated percentage energy savings to the baseline end-use loads to calculate the SAE High DSM Case load for that end-use.
(4) Sum across end-uses to calculate the total load for each BA.

[7] Barbose et al. [1] describe data used for these DSM adjustments and other details (including the adjustments in absolute GWh and MW terms).

4.2.2. Residential and commercial stock efficiency data sources and assumptions

As noted previously, the residential and commercial end-uses within the SAE load forecasting model largely correspond to those within NEMS. For each end-use, NEMS requires information about the range of efficiency levels currently available and projected to be available in the future. To develop stock efficiency assumptions for the High DSM Case, we relied primarily upon studies conducted for the EIA on present and future end-use technology characteristics [21–25]). For most residential and commercial end-uses, these studies identify commercially-available high efficiency options as of 2010, and these are the default values used to define average stock efficiency levels in 2032 for the High DSM case.[8]

However, for a number of end-uses, the 2010 high efficiency option reported in these studies is lower than the projected 2032 stock efficiency in the SAE baseline, or the SAE definitions of categories – i.e., the technologies within them – differ from their counterparts in NEMS and were thus not analyzed in the above-mentioned studies. In the former cases, where possible we used the EIA's projected high efficiency option for a future year (rather than for 2010); in the latter, it was necessary to develop the High DSM case stock efficiency assumption from other sources, including a recent report on ultra-high efficiency technologies and technical support documents from the U.S. DOE appliance standards program [26–29]).

4.2.3. Percentage adjustments to SAE baseline end-use efficiencies

4.2.3.1. Residential sector calculations. In both NEMS and the SAE model, residential-sector efficiency is described for some end-uses in terms of technical units – such as Coefficient-of-Performance (COP) or Seasonal Energy Efficiency Rating (SEER) – and for others in terms of unit energy consumption (UEC), either kW h per year or kW h per household per year. The 2032 high-efficiency benchmarks were used to calculate percentage improvements in these efficiency indices for the year 2032. For each WECC BA/LSE we can write the year 2032 baseline consumption as

$$Load_{Baseline\ 2032} = \sum_i Enduse_{iBaseline\ 2032}, \tag{2}$$

where both sides of the equation are in GW h. For end-uses with efficiency in technical units, the High DSM consumption was calculated as

$$Enduse_{iHighDSM\ 2032} = \frac{1}{1+\%\Delta Eff} \cdot Enduse_{iBaseline\ 2032}, \tag{3}$$

where $\%\Delta Eff$ is the percentage improvement in efficiency for the given end-use. For end-uses with efficiency in UEC terms, the High DSM consumption was calculated as

$$Enduse_{iHighDSM\ 2032} = (1-\%\Delta UEC) \cdot Enduse_{iBaseline\ 2032}, \tag{4}$$

where $\%\Delta UEC$ is the percentage reduction in the UEC for the given end-use. Combining both types, the total residential High DSM consumption for the given BA is then

$$Load_{HighDSM\ 2032} = \sum_i Enduse_{iHighDSM\ 2032}. \tag{5}$$

4.2.3.2. Commercial sector calculations. Although both are based on engineering-economic principles, the structure of the NEMS commercial module (sub-model) differs in certain details from that of the residential, including the representation of end-use efficiency. While the commercial module also uses technology input data including efficiencies in terms of technical units or UECs, these are converted within the model (for most end-uses) into the metric of btu-out/btu-in for the energy service demands computed by the model for a given scenario, and the module's end-use efficiency outputs are reported in terms of this metric. Furthermore, in the commercial module, the average efficiency for each end-use is a composite across different technology types providing the energy service within that end-use in contrast to the technical units or UECs that are typically used for residential end uses.

These differences are reflected in the calculations of end-use-level commercial High DSM savings. In the commercial module, the electricity consumption within each end-use – indexed by i – is the sum of consumption provided by the corresponding set of end-use technologies, indexed by *tech* (in the following formulae we suppress the time index for simplicity):

$$Enduse_i = \sum_{tech} Enduse_{i,tech}. \tag{6}$$

For each technology type, we used the "2010 high efficiency" level reported in the previously-cited studies for EIA (or a proxy), $Eff_{i,tech,high}$, and defined a consumption share-weighted high-efficiency level for 2032 as

$$Eff_{i,high} = \sum_{tech} \frac{Eff_{i,tech,high} \cdot Enduse_{i,tech}}{Enduse_i}. \tag{7}$$

The calculation of commercial 2032 High DSM load was then similar to that for residential sector represented in Eq. (5), above, but used this high-efficiency composite.

Tables 4 and 5 display the High DSM 2032 efficiency improvements in percentages for the residential and commercial sectors, respectively, by end-use and by "load groups" – sub-sets of BAs (grouped mostly by state and province) for which the underlying stock efficiency projections, and hence the High DSM savings factors, are equal. For the residential sector, these percentages are those referred to above as $\%\Delta UEC$ for end-uses with efficiency measured by *UEC*. For residential end-uses with efficiency measured by technical units, the percentages are given by $\%\Delta Eff/1+\%\Delta Eff$; commercial sector percentages are also given by the latter expression, where $\%\Delta Eff$ is the percentage improvement from the baseline efficiency to "$Eff_{i,high}$" (per Eq. (7)).

For both sectors, the reason for the pattern of equal efficiency improvements in percentage terms within (and in some cases across) load groups is several-fold. First, in the SAE baseline, 2032 efficiency levels are based upon those of U.S. Census Regions 8 and 9 in the EIA *AEO 2012* Reference Case, which results in a degree of geographically-based uniformity in baseline stock efficiency levels. Second, the "target" 2032 levels used to calculate the percentage improvements – including the EIA estimates described above – are in technical efficiency units or in terms of unit energy consumption. That is, they are absolute rather than incremental, and therefore result in uniform percentage increases when applied to the baseline values. Finally, variation in the percentage increases among load groups within the two Census regions results primarily from the use of local or regional information to adjust the EIA estimates within these load groups.

4.2.4. Industrial sector

For industrial load, a simpler procedure was used. The reason is that in contrast to the engineering-economics approach of the NEMS residential and commercial modules, the NEMS industrial load forecast module does not represent technologies, technology types, or end-use detail specifically, but instead uses a simpler and much more aggregated econometric forecasting structure,

[8] Current high-efficiency levels on the market are steadily increasing for a number of end uses, and at any given time, estimates as to what this level is for a given end use may vary. Thus, these studies' estimates were not interpreted as being definitive, but rather as reasonably comprehensive as well as conforming with the structure of the NEMS model, and therefore with the SAE framework.

Table 4
Residential sector High DSM percentage efficiency improvements in 2032 relative to SAE baseline.

End-use category	Units[a]	Load group							
		AZ, CO, NV, PACE UT-WY (%)	ID, MT, PACE ID (%)	NM (%)	CA (%)	WA, OR (%)	BPA (%)	PACW (%)	AB, BC (%)
Electric furnace	COP	57.4	57.4	57.4	57.4	59.7	59.4	59.4	57.4
Heat pump heating	HSPF	42.5	7.9	42.5	42.4	6.8	6.9	8.2	42.4
Ground-source heat pump heating	COP	21.9	21.9	21.9	21.9	21.9	21.9	21.9	21.9
Secondary heating	kW h/year	57.4	57.4	57.4	57.4	59.7	59.5	59.5	57.4
Cent air	SEER	37.9	38.9	37.9	38.1	38.9	38.9	38.8	45.6
Heat pump cooling	SEER	35.7	35.7	35.9	35.9	35.7	35.7	35.7	35.7
Ground-source heat pump cooling	EER	36.9	36.9	36.9	36.9	36.9	36.9	36.9	36.9
Room air	EER	11.4	11.5	11.4	11.5	11.5	11.5	11.5	8.8
Electric water heating	Energy factor	4.7	4.7	4.7	4.6	4.6	4.7	4.7	4.6
Electric cooking	kW h/year	6.0	5.5	6.0	6.9	4.9	4.9	4.9	6.9
Refrigerator	kW h/year	47.0	27.0	47.0	46.8	26.7	26.7	26.7	46.8
Secondary refrigerator	kW h/year	47.0	27.0	47.0	46.8	26.7	26.7	26.7	46.8
Freezer	kW h/year	27.6	36.4	27.6	28.1	36.2	36.3	36.2	28.1
Dishwasher	Cycles/kW h	38.1	36.0	38.1	38.1	35.3	35.4	35.6	38.1
Clothes washer	kW h/cycle (motor)	24.8	48.4	24.8	24.8	47.8	47.8	47.8	24.8
Electric dryer	Lbs/kW h	5.6	13.7	5.6	4.0	13.8	13.8	12.8	4.0
TV	kW h/year	53.4	53.6	53.4	55.7	55.7	55.5	55.7	55.7
Furnace fan	kW h/year	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
Lighting	kW h/household/year	51.4	51.4	51.4	52.3	52.3	52.2	52.3	51.4

[a] For load groups in the Pacific Northwest (ID, MT, PACE ID, WA, OR, BPA, PACW), the units for refrigerators (including secondary) and freezers are cubic feet cooled per kW h per day. See Nomenclature table for definitions of technical units.

Table 5
Commercial sector High DSM percentage efficiency improvements in 2032 relative to SAE baseline.

End-Use Category	Units	Load Group					
		AZ, ID, MT, NM, NV, PACE ID-UT-WY (%)	CO, UT, WY (%)	CA (%)	OR, WA, AB, BC (%)	BPA (%)	PACW (%)
Heating	COP	34.9	31.9	35.0	31.5	31.9	31.9
Cooling	COP	27.5	34.5	19.9	26.4	26.6	25.8
Ventilation	1000 cfm hours output/1000 btu input	63.7	64.2	57.6	63.4	63.4	62.8
Electric water heating	COP	19.2	25.9	34.1	34.7	33.4	34.6
Electric cooking	COP	1.8	1.8	3.0	1.8	1.8	1.9
Refrigeration	COP	45.5	45.5	59.8	47.2	47.0	48.5
Outside lighting	Lumens/watt	21.5	21.9	28.1	23.4	23.2	23.9
Interior lighting	Lumens/watt	21.5	21.9	18.4	23.4	23.2	22.9
Office	N/A*	24.9	24.9	24.9	24.9	24.9	24.9
Miscellaneous	N/A*	13.0	13.0	11.2	11.2	11.3	11.2

* See Section 4.2.3.2.

which is adopted in the SAE framework. For the 2032 High DSM industrial efficiency target, we assumed that SAE baseline industrial load would be reduced by 10% based on a review of recent energy efficiency potential studies [30–35]).

4.3. High DSM case energy efficiency savings

To calculate the High DSM incremental energy savings for each BA, the High DSM load forecast was subtracted from the corresponding SAE baseline forecast. As shown in Fig. 5, WECC-wide annual energy consumption in the High DSM Case is 21.6% lower than in the baseline. Incremental savings vary across the BAs, in most cases ranging from 15% to 25% of the baseline forecast, reflecting differences in end-use characteristics across BAs and regions. These savings are incremental to those already contained in the baseline, and constitute the difference between what is expected to occur under the current set of energy efficiency policies and program plans, and a more aggressive approach.

The residential and commercial sectors together represent the overwhelming majority of incremental savings relative to the baseline forecast, as shown in Fig. 6, which decomposes the savings by customer sector, for WECC as a whole as well as for each of three geographical regions. Compared to the residential and commercial sectors, the projected savings for the industrial sector were relatively low in the High DSM Case (i.e., a 10% reduction from baseline), and as a result, the industrial sector represents a disproportionately small part of the overall incremental savings. Between the residential and commercial sectors, each represents similar proportions of the total incremental savings, with savings in California and the Southwest skewed slightly towards the commercial sector and savings in the Northwest skewed slightly towards the residential sector.

The residential and commercial sector savings can be further decomposed by end-use, as shown in Fig. 7, which presents the distribution in residential and commercial sector savings across 10 major end-use groups. In general, the contribution from any

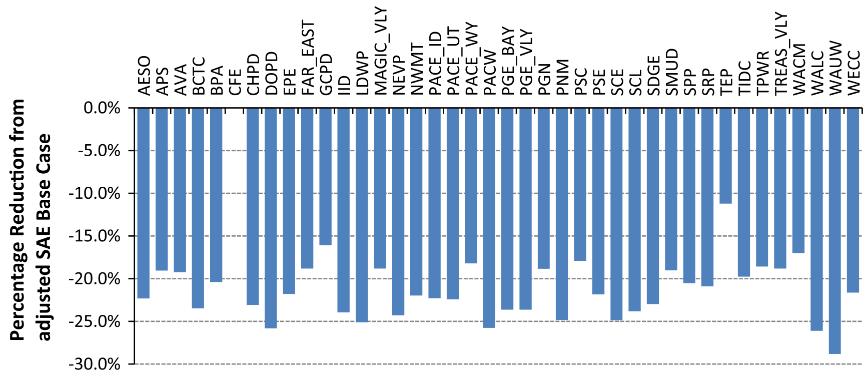


Fig. 5. SAE High DSM Case incremental savings relative to SAE baseline.

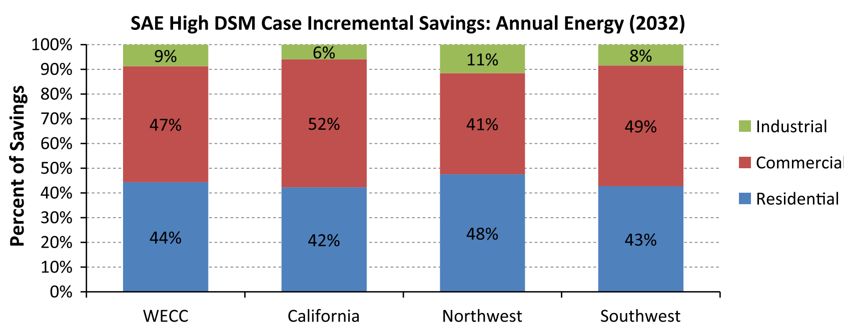


Fig. 6. SAE High DSM Case incremental savings by customer sector.

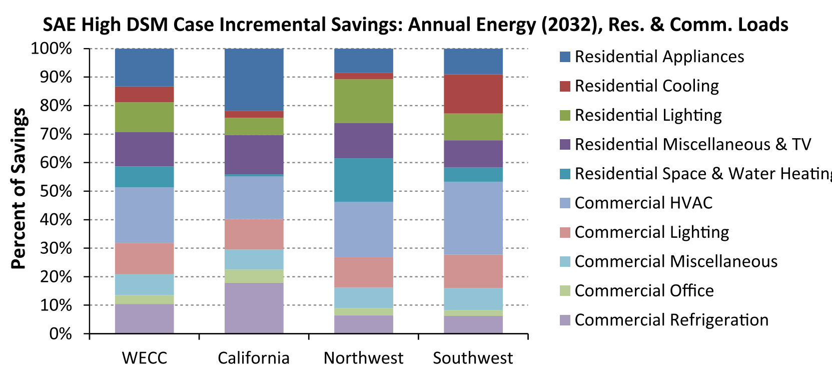


Fig. 7. SAE High DSM Case incremental savings by end-use group.

individual end-use is a function of both its share of total load in the baseline and the specified efficiency improvement between the baseline and the High DSM Case. The net effect of these underlying drivers, as shown in the figure, is that the savings are somewhat evenly distributed across end-uses, with six of the ten end-use groups each constituting 10–20% of the WECC-wide incremental savings. Commercial HVAC is the largest source of incremental energy savings for WECC as a whole (20% of the total), and either the largest or among the largest for each of the three regions (ranging from 15% to 26%). The significance of most other end-uses varies regionally, reflecting differences in regional climate and end-use saturation trends. For example, as to be expected, Residential Cooling is a major contributor to total incremental for BAs in the Southwest, while Residential Space & Water Heating is a major contributor in the Northwest.

5. Discussion and concluding remarks

The results we have presented on an aggressive long-term energy efficiency scenario for the WECC illustrate the advantages of the hybrid methodology relative to the application of either of its component elements. On the one hand, in contrast to a strictly econometric approach, the inclusion of explicit end-use detail even at less than complete disaggregation enables us to tie technology-specific information directly to the projected loads in both the baseline and the High DSM cases. On the other, the underlying econometric component facilitates the appropriate statistical representation of the effects of economic, weather, and other inputs. The heterogeneity of energy savings at both the BA and the regional level reflects in part this synergy.

Another advantage of the SAE framework relative to traditional econometric load forecasting methods has to do with the effects of end-use efficiency on peak demand. Efficiency measures can have different impacts on peak than on energy, and the SAE end-use disaggregation enables these differences to be represented and analyzed [1].

Advances in the treatment of energy-efficiency in load forecasting and in approaches to long-run transmission planning are examples of analytical methodologies both evolving in response to new energy policy priorities, and supporting the development of more ambitious and sophisticated policy designs. This paper has described an analysis in the intersection of efficiency modeling and transmission planning, reflecting the changing analytical and policy landscape. The "hybrid" load forecasting framework and its use in creating the "High DSM" scenario for the WECC's new planning initiative exemplifies the value of cross-cutting approaches. This work may provide a model for similar efforts as the implementation of efficiency programs continues and the demands on transmission planning practices increase.

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