Measuring Emission Benefits with Integrated Resource Models

Why Simple Estimates of Emission Reductions May Be Wrong

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ABSTRACT

Energy efficiency program administrators must account for the emissions displaced by their programs in order to accurately report achieved benefits. This paper examines three methods of calculating those displaced emissions. Emission reductions from three demand-side technologies were calculated with integrated resource models, capturing the hourly changes in power plant emission rates and end-use technology performance. Refined load shapes were developed to characterize the time-of-use for residential CFLs, commercial office building CFLs, and residential air-conditioning. Those load shapes were used within the integrated resource models to calculate refined emissions estimates. Results of the rigorous modeling were compared to estimates using flat load shapes (neglecting time-of-use) and estimates using system-average emission rates. Using system-average emission rates was shown to be highly inaccurate. Neglecting time-of-use also resulted in significant relative errors that varied with technology, pollutant, and supply-side system. Errors are lower for a system that consistently relies on a single fuel, because a poor characterization will still displace the correct fuel. Errors are considerably higher for systems that more frequently alternate between marginal fuels. In systems alternating between coal and natural gas, the error will be lowest for CO_2 and higher for SO_2, NO_x, and mercury. Errors when end-use load shape is neglected were as high as 17% for CO_2 and 180% for mercury. These results have bearing on policies that promote certifiable DSM emission reductions. Emission reduction estimates that neglect the hourly changes in marginal emission rates and the end-use technology's time-of-use are often inaccurate and occasionally invalid.

Introduction

Energy efficiency program administrators must account for the emissions displaced by their programs in order to accurately report achieved benefits. This work explores two modeling applications capable of precise emission reduction calculations using hourly power plant data. Both are integrated resource models, meaning they incorporate the performance of energy efficient technologies within a realistic simulation of supply-side generation.

Time-of-use data for demand side technologies is limited. This work uniquely tests whether refined load shape characterizations significantly improve demand-side technology assessment. Three end-uses are evaluated: residential CFLs, commercial office building CFLs, and residential air-conditioning. While the methods described are capable of assessing emissions and production cost savings, the demonstrations are applied exclusively to nitrogen oxides (NO_x), sulfur dioxide (SO_2), mercury (Hg) and carbon dioxide (CO_2) emission displacement.

This work compares the emission reduction estimated with refined load shapes and hourly production data to those estimated with simpler load shapes and average emission rates. The comparison of these results should be of great interest to program evaluators and regulators promoting certifiable DSM emission reductions. If the more detailed analysis significantly alters estimates of program benefits, this draws into scrutiny those estimates for which end-use load shape and marginal emission rates are not properly characterized.

Background

The idea of evaluating DSM programs within the supply-side framework is not new. Electric utilities initially coupled detailed end-use forecasting models with detailed production costing models. These models were intended for stand-alone use, and their integration was an onerous process. In the 1980s a new class of "integrated" planning models substituted less-detailed analysis of both supply and demand side processes into a single software platform (Eto 1990). As many energy efficiency programs moved out of the auspices of electric utilities, however, the program activities were also removed from those utility models most capable of measuring their supply-side impacts. Maintaining these modeling applications in non-utility programs is rarely viable, with requisite software license fees potentially ranging from US$30,000-200,000 annually, in addition to considerable staff and consulting time (e7 2000). In the absence of state-of-the-art modeling capabilities, program administrators use various screening metrics to select technology end-uses for various program objectives, of which emissions reduction is of increasing concern.

The simplest rational approach for measuring displaced emissions is to multiply the annual energy reduction by a system average emission rate. This "box-model" method, shown in Figure 1, assumes that efficiency measures displace electric generation across all power plants in proportion to their annual production. In reality, the efficiency measure displaces generation only from those plants operating on the margin (those plants actively changing power output to follow system load). The box-model neglects the daily and seasonal variation in emission reductions occurring from 1) changes in the marginally operating power plant, and 2) changes in demand-side load shape (i.e., time of use for end-use technologies).

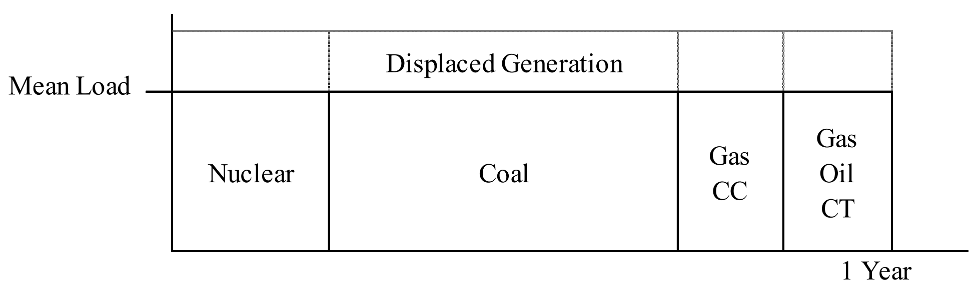

Figure 1. "Box-model" Neglecting Temporal Supply and Demand-Side Characteristics

The errors associated with using the simple average emission rates are large and demonstrated in this work. The simple box model can be improved by dividing the year into multiple seasons, subdividing each season into smaller segments, and calculating a mean emission rate for each period. This modeling effort can be further improved by using a load duration curve (LDC) model, which naturally incorporates a changing supply side fuel mix and the impact on marginal generation. LDC models are capable of incorporating demand side load shapes, but usually for a limited number of periods (Rahman et. al. 1996; Malik, 2001).

Increasingly detailed analysis can be achieved with models that are capable of varying data for each hour the year; however, these models will typically be constrained by the end-use data available to the analyst (Eto 1990). Two such models are used for this work, one evaluating hourly historic power plant data (Erickson et. al. 2004) and one simulating future power plant performance (Meier 2005). Data for demand-side time-of use is noticeably lacking from the literature. To serve as proxy for real demand side time-of-use data, refined load shape characterizations were constructed as engineering estimates. The models and load shape characterizations are described in the following section.

Methods

This work tests whether energy efficiency emissions assessment can be improved with refined end-use load shapes (i.e., time-of-use characterizations) and detailed power plant production analysis. Detailed load shapes for three technology end-uses were characterized under narrowly defined scenarios, as described in Section 3.1. The refined load shapes for each technology were incorporated into integrated resource models, capable of accounting for hourly changes in both marginal emission rates and end use load shapes. (This approach is referred to as "Method 1".)

As a basis of comparison, additional estimates of emission benefits were generated using two simplified approaches. In the first simplified approach (Method 2) emissions were estimated from the same hourly production models, but without refined end-use load shapes (i.e., load shape is assumed flat). The second simplified approach (Method 3) estimates emissions from the system-wide average emission rate (Box Model), and without refined end-use load shapes (i.e., load shape is flat).

Two models were utilized. The first model (the PA Emissions Model) is an historic hourly emissions model that tests the hypothetical reductions achieved by each end-use technology deployed within a set of Wisconsin generators, as defined by their actual 2000 performance (Erickson et al. 2004). The second model, FIDO, uses chronological hourly dispatching of a typical U.S. utility system to project hypothetical emissions reductions over the course of a 5-year electric generation expansion plan (Meier 2005). Modeling methods for the PA Model and FIDO are described in Sections 3.2 and 3.3 respectively.

End-Use Load Shape Construction

Detailed load shapes were characterized for three technology end-uses: low-income residential compact fluorescent lighting (CFL), commercial office building CFL, and residential air conditioning. The characterizations attempt to realistically divide the typical, or average, running hours of each technology into season, day type, and time-of-day. The divisions are based on characteristics of the end-use market and differ for each technology. The purpose of this paper is to test the implications of modeling methods. Simply stated, our concern is whether the incorporation of load-shape characterizations significantly alters the estimate of avoided emissions, not necessarily the precision of the load shape characterization itself. Therefore, each characterization was narrowly defined so that each load shape could precisely reflect a clear scenario. For example, we assumed the commercial office building was open Monday through Friday from 8 to 5, rather than trying to model a more complex scenario with some rooms occupied on nights and weekends. Statistical validation of load shapes is unwarranted for this paper, but may be justified for future work based on this study's results.

Residential CFL. The residential CFL load shape is based on a total annual average running time of 1,280 hours. The time of use characterization, illustrated in Figure 2, defines distinct periods of increased morning and evening use. Two seasons are differentiated, with slightly more use occurring earlier in the Winter evening than Spring/Summer/Fall. Two day-types are defined with weekend use shifted later in the day and having lower peaks and higher troughs than weekdays. The Y-axis represents the fraction of installed units that are operating, but may also be thought of as the probability of any given unit being on. In all load shape constructions, primary U.S. holidays are treated as weekend days.

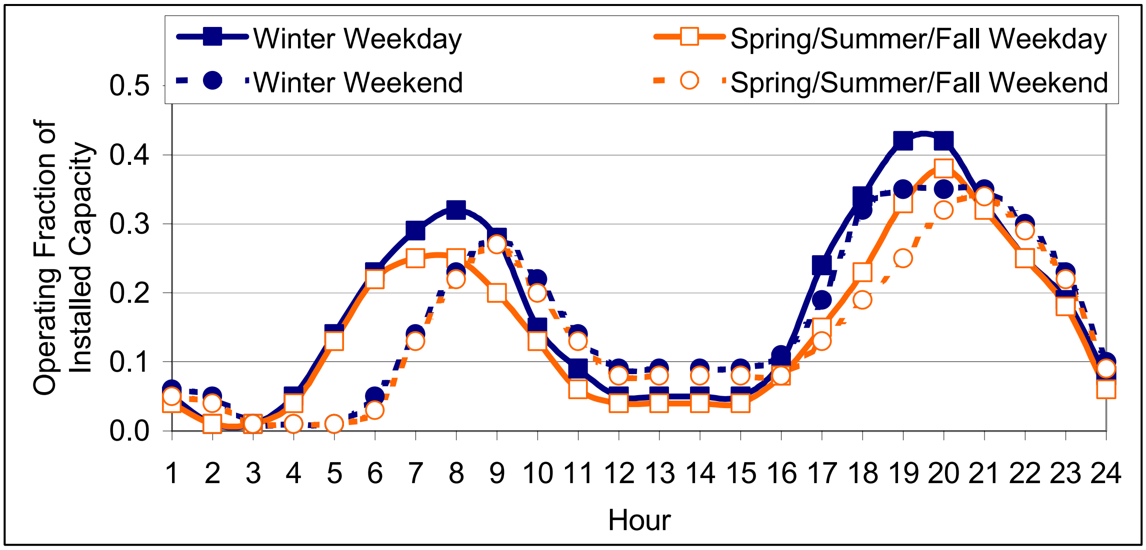

Figure 2. Residential CFL Load Shape Characterization

Commercial CFL. The second load shape is for CFL use in a commercial office building with occupancy during office hours on weekdays only. Only two day-types were constructed because weekday and weekend is an important division while season is not. A very specific building type is defined in Figure 3, with use heavily concentrated around 8:00 – 5:00 working hours, a secondary peak representing cleaning hours, and no weekend use.

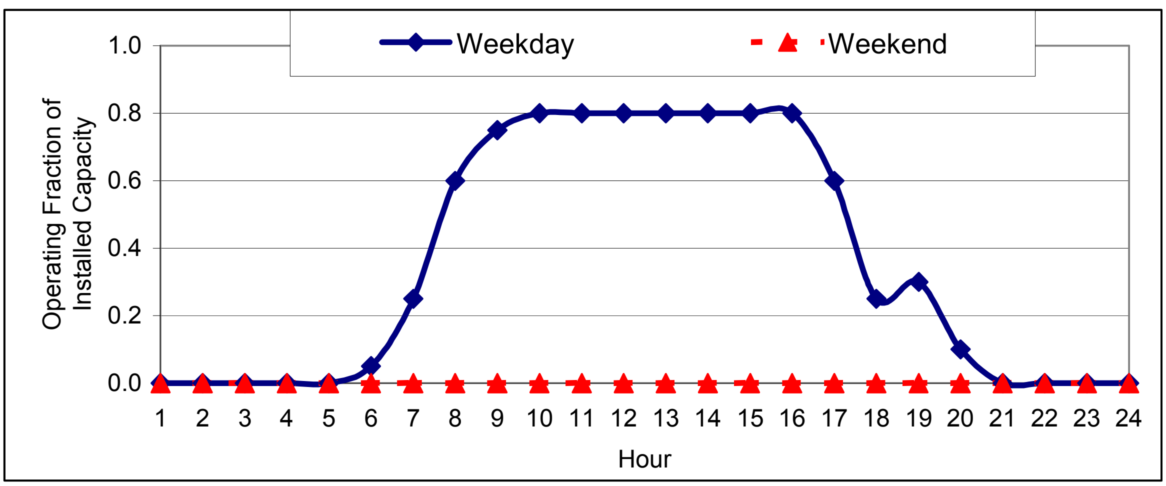

Figure 3. Commercial Office Building CFL Load Shape Characterization

Residential Air Conditioning. Load shape for residential air conditioning is shown in Figure 4, and is divided into three day types: cooling season weekday, cooling season peak day, and cooling season weekend. Peak days are defined as the highest 30 days of load, with residential air conditioners having an assumed maximum coincidence of 59% from 5:00 to 6:00 pm. We assume that air conditioning is operating during the day. No attempt is made to incorporate the synergistic impact of CFL and air conditioning. This may result in an underestimation of emission reduction (Eto 1990).

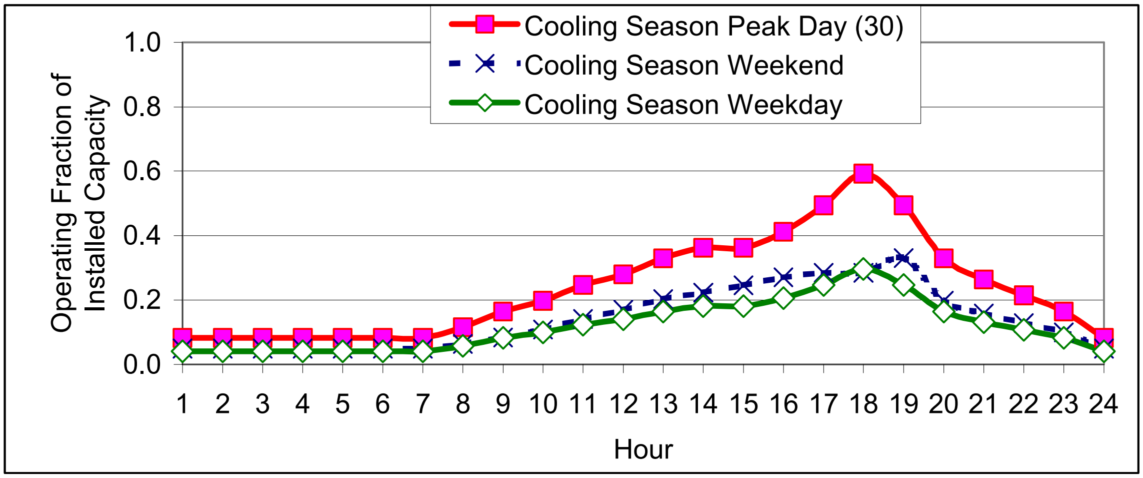

Figure 4. Residential Air Conditioning Load Shape Characterization

Historic Emissions Evaluation

The PA Emissions Model (PA Model) calculates emission factors for electric power generators using hourly measured emissions data. The PA Model uses hourly data EPA collects to monitor emissions at power plants. The model selects plants that were actually operating in specified seasons and times of the day, predicts which were the marginal producers for each hour, and then calculates emission factors from all marginal producers operating in the specified season and time of day. The PA Model calculates emissions factors for nitrogen oxides (NO_x), sulfur oxides (SO_2), carbon dioxide (CO_2), and mercury (Hg). The emissions factors are expressed as pounds of emissions per MWh of generation. The PA Model can calculate emission factors for any set of generation plants chosen, for example, by location or fuel type. The model can calculate emissions factors for any subset of the hours of the year, defined by seasons and times of the day. Thus, for example, it can calculate emissions factors for plants operating during the day on weekdays in the summer to estimate the impacts of programs targeted at reducing demand during those times, such as residential air conditioning programs.

The PA Model can be customized to examine any subset of generators to produce emissions factors that address specific needs. Thus it could model all US generators, all generators in a NERC region, in a state, or in a region of a state for example to examine emissions that might affect localized environmental issues, such as smog. For the results presented in this paper, the PA Model used only power plants physically located in Wisconsin and emissions data from 2000.

The PA Model uses actual hourly plant emissions to directly calculate emission factors. Other common approaches use data on generator characteristics (fuel, heat rate) to estimate hourly emissions or back into hourly emissions estimates using measured annual emissions data. This feature of the PA Model gives it a firm foundation for estimating emission rates for subsets of the year, defined by hours of the day and/or seasons of the year. We used this capability for this paper to calculate emissions factors for generators that are operating in the hours and seasons that correspond to the demand from the end use load shapes we defined. Thus, using the PA Model we can calculate total system load curves for Wisconsin corresponding to the hours and seasons defined for residential CFL use (Figure 5). We see highest demand in mid-day on a weekday in the summer when residential CFL use is fairly low and early evening in the winter on a weekday when residential CFL use is at its highest. Maximum emission rates all occurred in the night or early morning when demand is relatively low. The maximum emission rate for NO_x occurs in the middle of the night on a summer weekend (see the oval in the bottom right graph in Figure 5) when residential CFL use is quite low. Maximums for CO_2 and Hg occur between 5 and 9 am on summer weekends when CFL use is ramping up but is still well below its peak. Maximums for SO_2 occur in the middle of the night on a winter weekend. Minimum emission factors for all substances all occurred in the evening on winter weekdays when demand was particularly high and when CFL usage is at its highest.

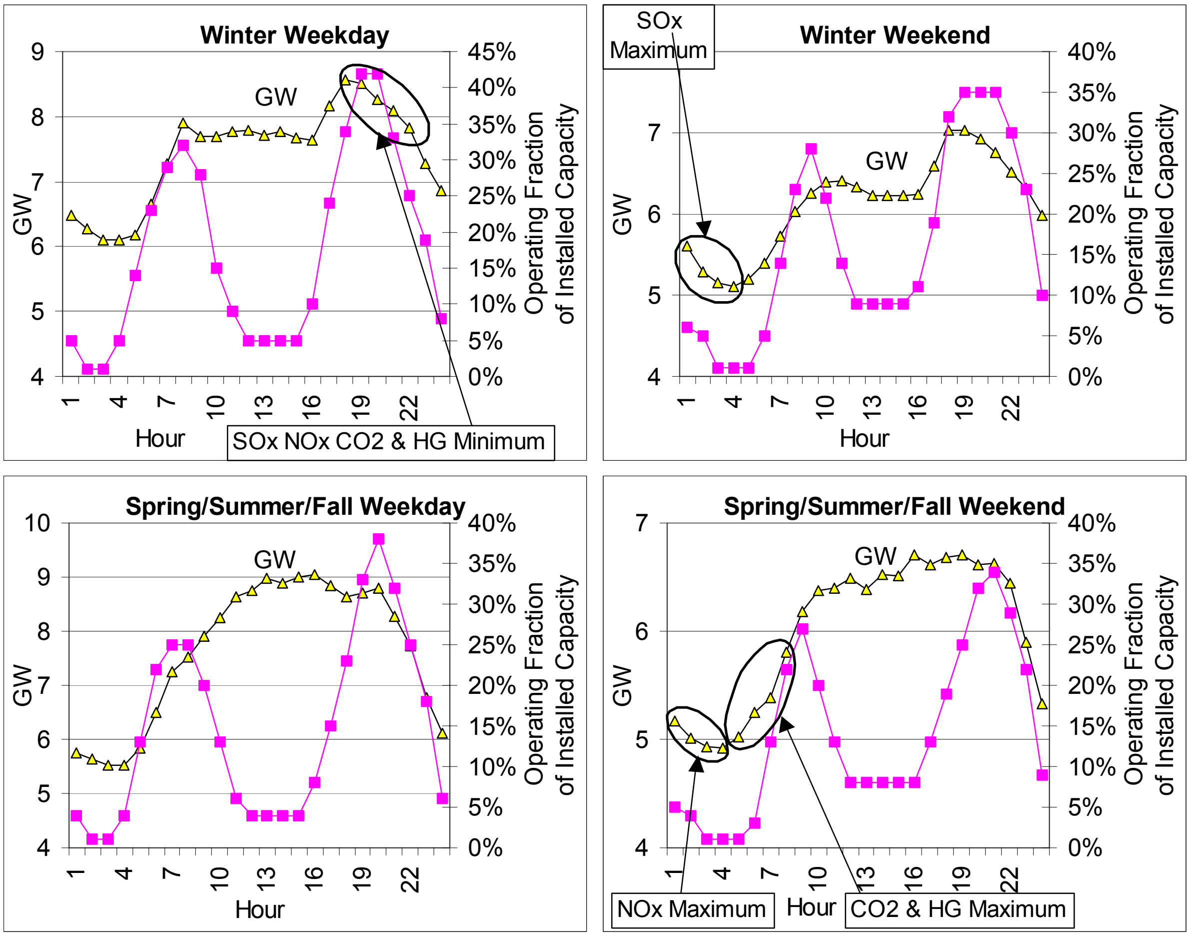

Figure 5. Residential CFL Load Shapes, Wisconsin Daily Load Curves, and Emission Rates

Because the peaks of residential CFL usage coincide with the lowest emission factors, and the highest emission factors coincide with relatively low CFL usage, the emissions profile of a program emphasizing residential CFLs in Wisconsin appears to be relatively unattractive. Analysis we present later in this paper will compare the profile of residential CFLs with commercial CFLs and residential air conditioning.

As indicated above, off-peak generation tends to be dirtier in Wisconsin. The primary reason is that Wisconsin relies very little on natural gas generation and coal is usually the marginal fuel, particularly in off-peak hours, as seen in Figure 6. In the middle of the night, coal plants are typically providing the vast majority of power. Even when we use the PA Model to look at power plants operating on the margin, coal still produces the majority of the power and accounts for the largest fraction of emissions. However, the fact that marginal emissions are not entirely from coal points the way to the benefits of using emissions models like those discussed in this report – the more accurately you can model the marginal emissions rate, the more accurately you can estimate the emissions profile of energy efficiency measures – even in systems like Wisconsin's that are heavily coal-dependent.

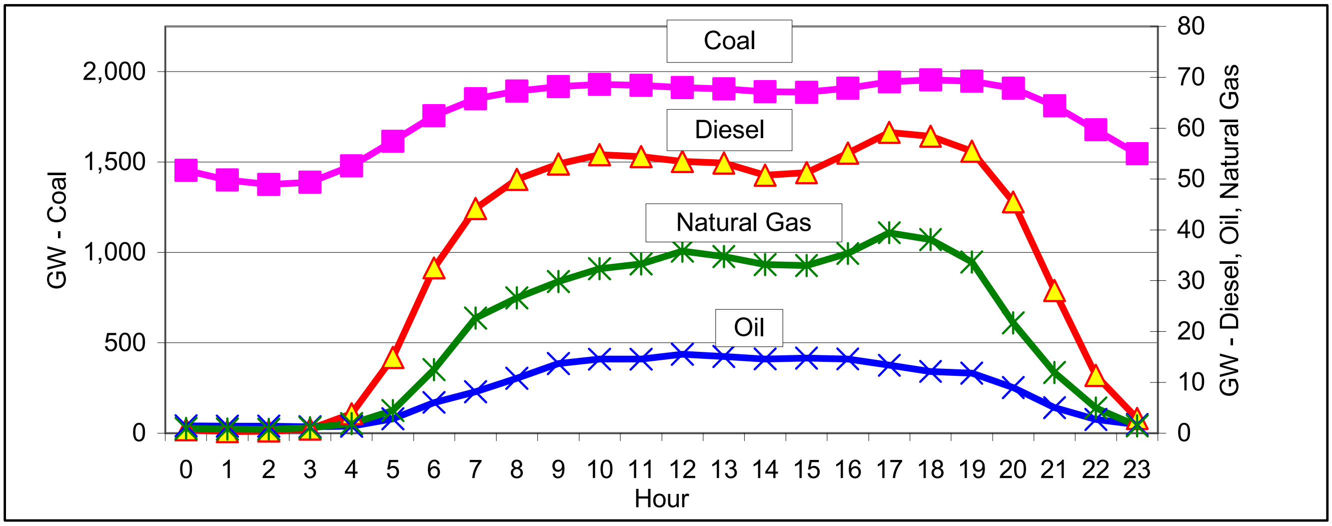

Figure 6. Wisconsin Generation Profile by Fuel (2000)

Future Emissions Estimation

The previous section describes the methods used for ex-post emissions evaluation for a given year. This section describes methods to predict future emission reductions occurring over a 5-year generation expansion plan. The end-use load shape characterizations defined in Section 3.1 were tested using FIDO, an integrated planning model performing chronological hourly dispatching. To serve as the supply-side of the model, a typical utility system was constructed with baseline peak demand of 3,500 MW, annual energy consumption of 18,000 GWh, and a fuel-mix that roughly resembles the U.S. average. In contrast to the Wisconsin system modeled above, a typical U.S. system relies less on coal, and more on natural gas. While peak demand and total energy consumption were assumed to grow at 2% per year, the model maintains a 15% reserve margin requirement by installing supply-side and demand-side technologies as defined in the Table 1 expansion plan.

Table 1. 5-year Electric Generation Expansion Plan (MW Installed)

	Supply-Side Power Plants						Demand-Side Technologies		
Year	Hydro	Wind	Nuclear	Coal	Gas CC	Peaking	CLT	RLT	RAC
2005	200	100	350	1200	500	1325	4	4	4
2006	200	**150**	350	1200	500	1325	4	4	4
2007	200	150	350	1200	**750**	1325	4	4	4
2008	200	**200**	350	1200	750	1325	4	4	4
2009	200	200	350	1200	750	**1475**	4	4	4

CLT = commercial office building CFL; RLT = residential lighting CFL;
RAC = residential air conditioning

The FIDO model operates by constructing the chronological hourly load for a week, efficiently dispatching the available resources, and repeating the process for each week of the simulation. Energy efficient resources are modeled as equivalent generating units (Malik 1998), and are dispatched first. Hydroelectric capacity is optimally dispatched to run during the highest load periods of each week.

Remaining units are dispatched in ascending order of their marginal production cost: wind, nuclear, coal, gas combined-cycle, gas peaking. Wind is dispatched using modeled output generated using the HOMER Optimization Model for Distributed Power (NREL 2005). The renewable portfolio increases from approximately 7% - 9% over the modeled time period.

Power purchase decisions are made based on a variable hourly market. The simulation purchases power if it is less expensive than the next available unit, or if the next available unit cannot maintain a 25% capacity factor over a 4 hour time period (i.e., to avoid start-up and cycling costs). The system's transmission system has a 500MW import capacity, but is assumed constrained up to 15% during periods of highest demand. Purchased power is further constrained by modeling a realistic requirement for a "local" plant to follow load. Because displaced generation and associated emissions are occurring from this local plant, the uncertainty of fuel source from purchased power does not alter emissions estimates.

Figure 7 illustrates FIDO's dispatch of power plants on a summer day in 2008 (Top Plot). A coal plant is initially on margin, but as load increases, combined-cycle gas is dispatched, followed by peaking plants. Purchased power is interrupted in mid-afternoon, when it is more economical to dispatch a second peaking unit. Peaking plants are shut down in the evening, and combined-cycle gas returns to the margin. Marginal emission rates change in association with the dispatch, and are shown for CO_2 in the Center Plot of Figure 7. The marginal rate is distinctly higher when coal is on margin, as compared to combined-cycle of simple-cycle natural gas. This difference is more pronounced when emission rates vary dramatically between fuels (e.g., mercury for which the gas emission rate is zero).

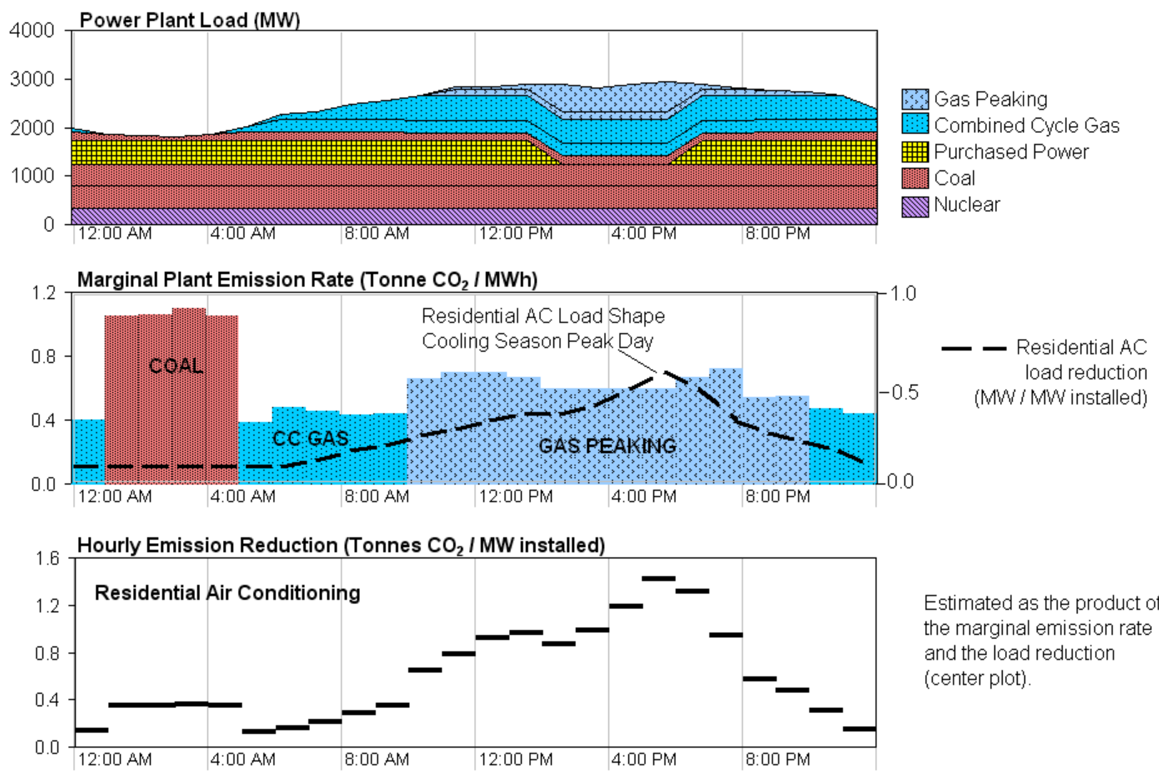

Figure 7. FIDO Modeling Illustration – Hourly CO_2 Reductions Achieved per MW of High Efficiency Residential Air Conditioning Installed. Simulation data is for June 8, 2008. Renewable generation is omitted for illustrative purposes only.

Figure 7 illustrates how emission reductions can be attributed to a demand-side end-use technology. The load displaced by 1MW of installed residential air conditioning is overlain on the Center Plot, as defined by the refined load shape characterized in Section 3.1. Emissions reductions (Bottom Plot) can be calculated by multiplying the marginal emission rate and the displaced load (Center Plot). Careful examination of the Bottom Plot reveals how the emission reductions are a combination of both the marginal emission rate and the end-use load shape.

Emissions are estimated based on the fuel-specific emission rates, shown for marginal plants in Table 2. Emission rates are adjusted to account for changing thermal efficiency using heat rate curves for each plant. The minor fluctuations in emission rate caused by heat rate effects are visible in Figure 7.

Table 2. Fuel-based Emission Rates for Marginal Plants (lb/MMBTU)

Pollutant	Coal	CC Gas	New Peaking	Existing Peaking
NO_x	0.45	0.0090	0.033	0.11
SO_2	0.90	0.00050	0.00050	0.0060
CO_2	212	115	115	115
Hg	4.5E-06	0	0	0

FIDO calculates the demand-side emissions reductions by running the 5-year simulation both with and without the energy efficient technologies. First, a baseline scenario is run in which no demand side measures are installed. The simulation is then re-run with a given demand side measure implemented. The change in emissions between the two scenarios is the net reduction.

Results

Refined load shapes were constructed for three energy efficient technologies. The performance of these technologies was integrated within hourly production models to generate an accurate estimate of emissions reductions achieved per MWh of energy saved. Results for Wisconsin generators and a typical U.S. utility are shown in Table 3.

Table 3. End-use Emission Reductions Estimated with Refined Load Shape Characterization and Hourly Production Modeling (Method 1).

	Wisconsin Generators, 2000			**Typical U.S. Utility, 2005 – 2009**		
Emission Reduction per MWh saved	Residential CFL	Commercial CFL	Residential AC	Residential CFL	Commercial CFL	Residential AC
NOx (kg/MWh)	-2.44	-2.02	-2.12	-0.42	-0.25	-0.40
SO_2 (kg/MWh)	-4.73	-3.28	-3.96	-0.74	-0.34	-0.51
Hg (mg/MWh)	-2.23	-1.89	-1.80	-4.1	-1.9	-2.8
CO_2 (kg/MWh)	-1,022	-972	-961	-584	-525	-588

Emission reductions are higher for the Wisconsin system, reflecting a higher reliance on coal as the marginal fuel. The typical U.S. emission reduction is smaller because natural gas, with lower emission rates, is more frequently on margin. Wisconsin's predominant coal use also results in less variability between the emission rates of different technologies. In other words, coal generation is usually being displaced, regardless of which technology is being evaluated. For both systems, emission reductions are highest for residential CFLs. This technology primarily operates in the evenings, when total system load is lowest and most likely to rely on coal generation.

Table 4 compares the rigorous Method 1 emission estimates to estimates generated using the following simpler approaches:

- Method 2: Emission rates estimated from marginal hourly supply-side emissions, but without refined end-use load shapes (i.e., load shape is flat).
- Method 3: Emission rates estimated from the annual average emission rate (Box Model), and without refined end-use load shapes (i.e., load shape is flat).

Table 4. Relative Error of Methods 2 and Method 3, compared to Method 1.

Emission Reduction per MWh saved	Method 2 Relative Error Wisconsin, 2000	Method 2 Relative Error Typical U.S., 2005-2009	Method 3 Relative Error Wisconsin, 2000	Method 3 Relative Error Typical U.S., 2005-2009
Residential CFL				
NOx (kg/MWh)	2%	21%	-38%	138%
SO_2 (kg/MWh)	2%	25%	-41%	180%
Hg (mg/MWh)	4%	25%	-23%	205%
CO_2 (kg/MWh)	1%	5%	-28%	22%
Commercial CFL				
NOx (kg/MWh)	12%	100%	-25%	297%
SO_2 (kg/MWh)	31%	169%	-14%	503%
Hg (mg/MWh)	10%	180%	-9%	580%
CO_2 (kg/MWh)	-3%	17%	-25%	36%
Residential AC				
NOx (kg/MWh)	-14%	19%	-29%	149%
SO_2 (kg/MWh)	-12%	71%	-29%	310%
Hg (mg/MWh)	-17%	75%	-4%	352%
CO_2 (kg/MWh)	-3%	3%	-24%	22%

Method 3 shows the largest errors compared to Method 1, but Method 2 errors can still be significant. Errors for the Wisconsin system are lower than those for the typical U.S. utility, because the marginal emission rate and average emission rate are both largely based on coal generation. This observation points to the fact that the Method 3 approach would be valid for systems relying exclusively on one fuel. The Method 3 error is greatly magnified in the U.S. system, where the average emission rate differs significantly from the marginal emission rate.

The discrepancies between Method 1 and Method 2 are dependant on system, pollutant, and end-use technology. An illustration of this error is presented in Figure 8 for Residential CFLs. Power plant load and marginal emission rate are shown in the top and center plots respectively. The refined load shape of Method 1 and the flat load shape of Method 2 are overlain on the center plot. The bottom plot shows hourly emissions reductions calculated as the product of the marginal emission rate (same for both Methods) and the load shape. Because Method 2 neglects changes in the end-use load shape, its emission reduction profile simply corresponds to changes in the marginal emission rate. Method 1 correctly captures the combination of load shape and marginal emission rate.

As with Method 3, the Method 2 errors are also lower for the Wisconsin system and higher for the typical US system. As explained above, this is due to less variability in Wisconsin's predominantly coal-powered system. Errors in characterizing end-use load shape are diminished in Wisconsin because even a poor characterization is still displacing the correct fuel (coal). A typical U.S. utility will alternate frequently between coal and natural gas on margin, thus errors in characterizing end-use load shapes are exaggerated by the displacement of the wrong fuel. The magnitude of the Method 2 error depends on the difference in emission rates between the marginal fuels. The errors are smallest for CO_2 because emission rates for coal and gas power plants differ by only a factor of 2 or 3. In comparison, NO_x, SO_2

and Hg emission rates for coal and gas vary by over 2 orders of magnitude, resulting in correspondingly higher errors.

Differences between the relative errors of different end-use technologies are significant. For the average U.S. utility, commercial lighting use coincided largely with natural gas generation. This resulted in a large error when load shape was neglected and the emission reduction occurred across both coal and gas generators. For the Wisconsin simulation, residential lighting use coincided largely with coal generation. This results in a small relative error because neglecting load shape still results in displacing primarily coal emissions. In the Wisconsin example, Method 2 accurately estimates CO_2 emissions, and all emission reductions from Residential CFLs.

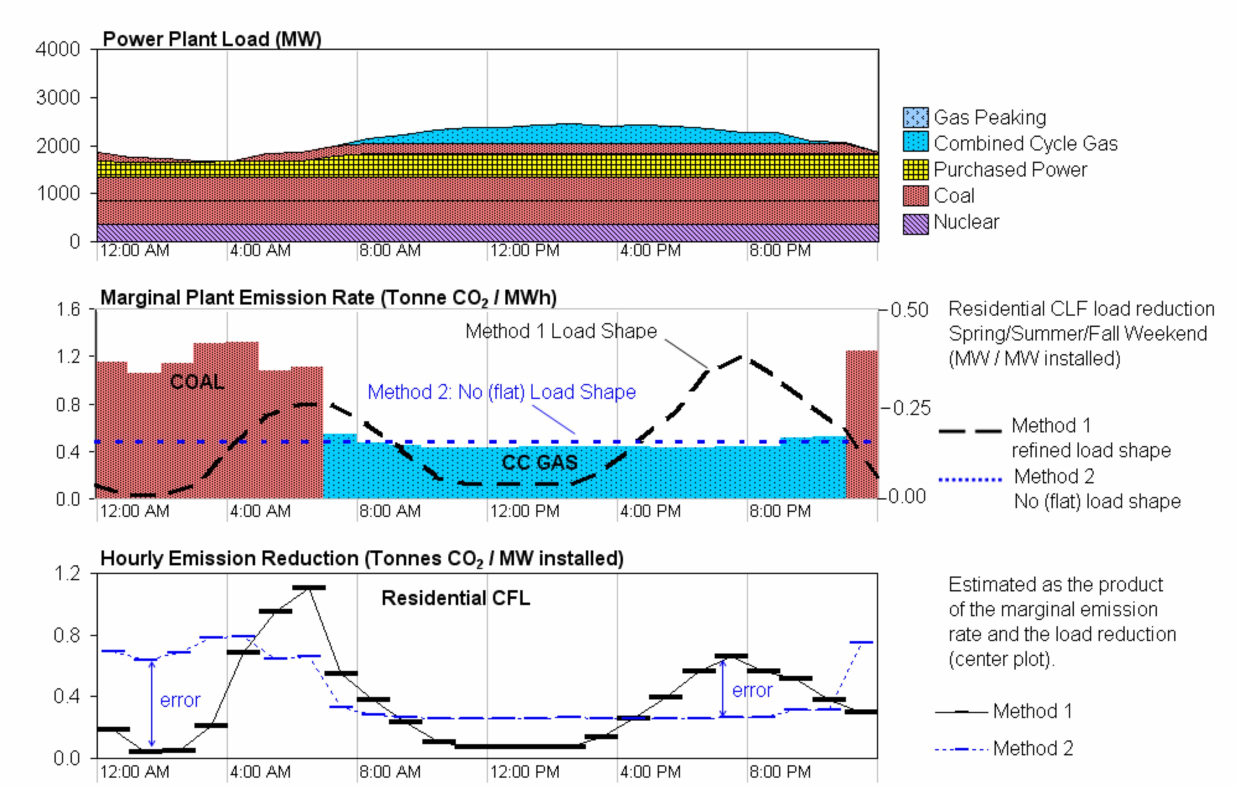

Figure 8. Illustration of Discrepancy Between Emissions Analysis with and without Refined End-Use Load Shape - Hourly CO_2 Reductions Achieved per MW of Residential Compact Fluorescent Lighting Installed.

Conclusions

Refined load shapes characterizations were developed for three end-use technologies, Residential CFLs, Commercial CFLs, and Residential Air Conditioning. These load shapes were incorporated into integrated hourly production models to calculate precise emission reductions from each end-use technology (Method 1). Results were compared to emission estimates generated using two simplified approaches, one neglecting end-use load shape (Method 2), and one neglecting both end-use load shape and marginal emissions (Method 3).

Method 3 used a system-average emission rate to estimate emission reductions and was shown to be highly inaccurate. This method is potentially appropriate for systems relying on one fuel; otherwise estimates should be based exclusively on the emissions from power plants operating at the margin. Even when considering only marginal emissions, estimates may be significantly inaccurate if the end-use load shape is neglected (Method 2). The magnitude of error is highly system specific and is affected by the variability of the plants on margin and the relative difference between fuel-specific emission rates. Errors are lower for a system that consistently relies on single fuel, because a poor characterization will still displace the correct fuel. The error is considerably higher for a system that more frequently alternates between marginal fuels. The magnitude of error is exacerbated when fuel-based emission rates vary greatly. In systems alternating between coal and natural gas, the error will be lowest for CO_2 and higher for SO_2, NO_x, and mercury. Errors incurred when end-use load shape is neglected were as high as 17% for CO_2 and 180% for mercury.

Hourly integrated resource modeling was shown to significantly improve emission estimates and efforts to better characterize demand-side load shape also appear justified. Accurate emissions benefits analysis reduces planning errors and theoretically improves a program's overall resource procurement process. Perhaps more importantly, a rigorous approach improves the validity of certifiable DSM emission reductions and credits trading.

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