Residential emissions reductions through variable timing of electricity consumption

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Abstract

A real-time electricity emissions estimating tool, the Locational Marginal Price Emissions Estimation Method (LEEM), is assessed for its ability to reduce emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), global warming potential measured as carbon dioxide equivalent (CO_2e), mercury (Hg), and lead (Pb) on a residential scale. Through LEEM, residential electricity use can be shifted to low emissions times of day. In the study area of Michigan, USA emissions from five types of appliances (hot water heater, refrigerator defrost, dishwasher, clothes washer, and clothes dryer) were calculated to be theoretically reduced by 21-35% annually through a “best-case” application of LEEM. Annual emissions of the five pollutants, SO_2, NO_x, CO_2e, Hg, and

Pb, can be reduced across the state by 429000, 110000, 87240000, 2.21, and 4.53 pounds, respectively – all without a reduction in the electricity used in the period of study. Despite different fuel mixes, similar emissions reductions were calculated for other regions of the country, as well.

Keywords
Emissions, Electricity, Residential, Demand Response, Michigan, Climate

1. Introduction

Power utilities continuously respond to changing electricity demand by dispatching or shedding generator output. In open markets, the price queue that is used to incentivize or discourage generation is the Locational Marginal Price (LMP). The LMP is the wholesale cost to serve the next incremental unit of load at a particular time and place. LMPs are published periodically in real-time (RT) as well as day-ahead (DA) projected prices.

Demand response is the ability of electricity consumers to reduce their loads in response to information signals such as information pertaining to peak load, high cost periods, or when system reliability is in jeopardy. According to a 2009 FERC Report, the residential class represents the "most untapped potential for demand response" [1]. With RT and predictive DA emissions estimates, residential customers can make informed decisions about the timing of the use of electricity-consuming devices.

In this work, probability distribution functions were used to tie RT and DA LMPs to four generator types: fuel oil, coal, natural gas, and a combined group of low cost, low emissions sources of electricity, which we have classified here as nuclear/renewable/hydro [2,3]. Each generator has a unique profile of air emissions based on the type of fuel consumed, efficiency of the equipment, and the type of pollution controls installed. This linked pricing and emissions information was developed into the LMP-Emissions Estimation Method (LEEM), which can be used to predict marginal emission rates [2,3]. By selecting the commercial pricing node located closest to a point of interest, LEEM provides the user with an estimate for the marginal generator and the marginal emissions. LEEM currently covers the same territory covered by the Midcontinent Independent System Operator (MISO) with four distinct fuel types, which are linked to marginal electricity prices through a probability distribution function. Details on the LEEM Version 1.0 and 2.0 methodologies are provided by Carter et al. [2] and Rogers et al. [3], respectively.

The work presented here builds on earlier work that links LMPs with emissions. Wang et al. [4] used LEEM to drive an apportionment of electricity loads among several locations to minimize emissions. CO_2, SO_2, and NO_x were all reduced by a LEEM-based spatial shift in load more strongly than a strategy based on minimizing LMPs alone. LMPs were also used to determine the effect of electricity trading between Quebec with New York and New England on CO_2 emissions [5]. In this study, LMPs were linked to fuel type and then used to compare the relative emissions rate for Quebec over a three-year period.

A bidding strategy for electricity generating companies that optimizes both cost and emissions was modeled by Vahidinasab and Jadid [6]. They demonstrated that emissions and costs can be optimized simultaneously with benefits to both. Long-range marginal emission factors for CO_2 were modeled in the British electricity system based on expected changes to fuel mixes and power plants where an increase in low-carbon generator types is expected to drive changes marginal fuel types and marginal emission factors [7].

Valenzuela et al. [8] compared dynamic electricity pricing (excluding emissions) with user behavior with respect to time-flexible tasks. When high response rates were accounted for, additional issues were observed in the simulation including increased congestion and shifted load profiles.

In this paper we explore how LEEM 2.0 can be used to time electricity loads as a way to reduce overall air emissions from the residential sector. The main contributions of this paper are (i) quantitative single home and regional emissions reductions estimates based on emissions driven demand response (ii) a comparison of real-time and day-ahead LMPs and (iii) emissions reductions modeled and compared across three regions to explore the impacts of fuel mixes and regional emission factors on a demand response emissions reduction program.

2. Methodology

The study area is the state of Michigan. Emissions calculations come from the ReliabilityFirst Corporation – Michigan (RFCM) subregion of the U.S. Environmental Protection Agency's (EPA) Emissions and Generation Resource Integrated Database (eGRID) [9], which covers roughly the geographic area of Michigan's lower peninsula. The study year is 2009, which is the most recent year for which we have a nearly complete data set.

The selection of electricity consuming devices was limited to five appliances whose use was deemed "shiftable" in time. Many of these appliances could be placed on an automated controller set to run only when emissions would be minimized, however most appliances currently in residential use require user intervention to adjust the timing of when units run. For the purposes of this project, the appliances analyzed were the water heater, refrigerator defrost cycle, dishwasher, clothes washer, and clothes dryer. It was assumed that consumers would be unwilling to change the timing of the use of other electricity-consuming devices such as entertainment equipment, lighting, and other common appliances such as the stove. Notably, heating, ventilation, and air conditioning (HVAC) equipment was excluded from the study. Although HVAC equipment represents the largest portion of home energy use [10] and shows great potential for emissions reductions, a significantly more in-depth analysis including accounting for weather would be required to portray accurately the effect of the timing of HVAC on emissions.

A base case household was defined and the timing of the five household appliances was explored to estimate the emissions reduction potential from a single family home. A comparison of RT and DA-driven emissions reductions was performed as was an order-of-magnitude assessment on a regional scale. All emissions are estimated based on LEEM 2.0 [3]. Simulations were built in Microsoft Excel 2007.

2.1 Base Case – Single Family Home

The creation of an "average household" provided a basis for estimating the effect of timing the use of the five household appliances on emissions. For the purposes of this study, the base case household was assumed to be similar to the average residential customer of DTE Energy, a utility serving the study area of Southeast Michigan. At the time of the study (2011), the average DTE Energy residential customer's electricity bill was $85.00 per month corresponding to a consumption of 23 kWh/day [11]. This relates well to the average energy use of 23.8 kWh/day for all Michigan residents in 2009 [10]. The base case analysis assumes all appliances run on the preferred schedule shown in Table 1.

2.1.1 Electric Water Heater

Electric hot water heaters were identified as a convenient appliance to selectively time based on emissions. Although most hot water heaters run on natural gas, 21% of hot water heaters in Michigan are electric [10]. Commonly, electric hot water heaters cycle once each hour to ensure hot water is continuously available [12, 13]. These cycles last about six minutes and draw approximately 5500 watts [12, 13]. Load control programs have been initiated by a number of utilities and programs that prevent electric hot water heaters from turning on for a set period of time during the day; commonly this is an approximately 6-hour power interruption, often during peak electricity consumption (1pm – 7pm) [13]. In this study, we use a 6-hour power interruption with a preferred shut off time of 1-7pm in order to test the emissions reduction potential of load shifting in a hot water system.

2.1.2 Refrigerator Defrost Cycle

The refrigerator defrost cycle, like an electric hot water heater, is a prime candidate for an automated controller that allows the equipment to run when emissions are lowest. This controller could be incorporated into existing technology that allows refrigerator defrost cycles to avoid periods of peak electric demand [14] or high emissions. The defrost cycle varies widely for different ages and models of refrigerators. A draw of 450 watts for the defroster is used by the U. S. Department of Energy (DOE) for a variety of models [15] and is assumed for this study. A defroster typically runs every 12 hours of compressor run time. Depending on weather, insulation, and door openings, this can vary in time from 12 to 84 or more hours [15]. The default for the US EPA refrigerator analysis (ERA) is every 10 hours, and for refrigerators equipped with higher efficiency adaptive defrost, the defrost cycle runs every 38 hours [15]. For the purposes of this project, we use the midpoint between 10 and 38 hours, or every 24 hours. The US EPA refrigerator analysis model assumes a run time of 10 minutes, which we also apply here [15]. The average Michigan home has 1.24 refrigerators [10].

2.1.3 Dishwasher

Dishwasher use is not as invisible to consumers as the hot water heater and refrigerator defrost cycles, but use of dishwashers can reasonably be shifted in time. The dishwasher was assigned an energy use of 1200 watts with a cycle length of 1.9 hours [16]. The average household runs their dishwasher 0.47 times per day [17]. In Michigan, 50% of homes have a dishwasher [10].

2.1.4 Clothes Washer

In the present analysis we adopt an average clothes washer use of 312 loads per year, or 0.86 loads per day [18]. An energy draw of 550 watts and cycle length of 0.49 hours/load were assumed for the washer use [16]. In Michigan, 82% of homes have a clothes washer [10].

2.1.5 Clothes Dryer

The analysis of clothes dryers is based on an energy draw of 5000 watts during use [16, 19]. In a 2012 survey, 89.2% of washer loads were dried in a dryer [17], corresponding to 0.76 dryer loads each day. The length of one cycle is approximately 0.70 hours [16, 17]. In Michigan, 45% of homes have an electric dryer [10].

Appliance	Frequency (cycles per day)	Cycle Length (hrs)	Power (kW)	Energy/ cycle (kWh)	Preferred Time Hr (1 - 24)	Appliances per Home
Water Heater	18	0.10	5.5	0.55	1-13; 20-24	0.21
Defrost Cycle	1	0.17	0.45	0.077	1	1.24
Dishwasher	0.47	1.9	1.2	2.3	22	0.50
Clothes Washer	0.85	0.49	0.55	0.27	19	0.82
Clothes Dryer	0.76	0.70	5.0	3.5	20	0.45

Table 1. Base case frequency of use, cycle length, power draw (wattage), energy consumed/cycle, "preferred time," and number of appliances per home for each of the five appliances [10, 12, 13, 15, 17, 18, 19]. Hour number corresponds to (time = x-1), i.e. 1 = 00:00 hrs, 4 = 03:00 hrs, 19 = 18:00 hrs, etc.

2.2 Emissions Calculations – Base Case

Applying the LEEM methodology, we can explore the potential changes in emissions if residential users time their electricity use to optimize emissions reductions. The base case home was compared with a best-case scenario, which assumes fully optimized emissions reductions for all five appliances included in the study.

Historical hourly-averaged LMP values were used for the test year of 2009 from a node located in Monroe, Michigan inside the DTE Energy service footprint. Fuel price ranges were defined using LEEM 2.0 [3] and were used to assign hourly marginal emission rates to each hour of 2009.

Five pollutants were included in this study: sulfur dioxide (SO_2), nitrogen oxides (NO_x), global warming potential calculated as carbon dioxide equivalent (CO_2e), mercury (Hg), and lead (Pb). Five distinct scenarios were generated – each scenario minimized one of the target pollutants. As an example, Table 2 shows the emission rate of NO_x at various hours of the day.

Day	Hr07	Hr08	Hr09	Hr10
1/1/09	2.31	0.487	2.31	2.31
1/2/09	2.31	0.487	0.487	2.31

1/3/09	0.487	0.487	0.487	2.31
1/4/09	0.487	0.487	0.487	24.59

Table 2. Sample emission rates of NO_x (lbs/MWh). Node in Monroe, MI, 2009.

To create a best case scenario, each hour of a specific day was assigned an "emission ranking" of 1 through 4 depending on which of the four fuel types was in use. One represents the lowest possible emission factor of the four fuel types and 4 represents the highest possible emission factor of the four fuel types for the specific target pollutant. Using the ranking, the algorithm selected the best possible operating hour for each appliance to run. When many hours have the same ranking, a "preferred time" was assigned to each appliance with the algorithm automatically selecting hours closest to the preferred hour of operation listed in Table 1.

The emissions (in pounds) of a specific pollutant for one cycle of operation for each appliance is calculated as follows:

$$\textit{Emissions (lbs)} = \textit{wattage (kW)} \text{ x } \textit{EF (lbs/kWh)} \text{ x } \textit{cycle time (hrs)} \qquad (1)$$

where EF is the emission factor of a specific pollutant as defined in LEEM 2.0.

Residential customers in Michigan used 8695 ± 496 kWh/year per household in 2009 (average ± standard deviation) [8]. The calculated energy use of the five tested appliances was 5092 kWh/year, representing 58.6% of the total household electricity use. Michigan had 3.8 million residential electricity customers in 2009 [10].

2.3 Real-time vs. day-ahead information

To schedule appliance use, residents must rely on projected DA LMPs, which are published daily. For the second part of the analysis, a best-case operating schedule was determined as before, only this time it was based on hourly-averaged DA information instead of hourly-averaged RT LMPs. Results for DA and RT LMPs were compared to determine how well correlated predictive and real-time information is.

2.4 Regional emissions reductions

In the third part of the study, the analysis was expanded to explore the potential environmental impact of a LEEM-based emissions reduction strategy on a regional scale. The State of Michigan was examined for the test year of 2009. The emissions reductions found for a single home were applied across homes in the state. The number of appliances per household are shown in Table 1. It should be noted that Table 1 accounts for electric appliances only; gas hot water heaters and gas dryers are excluded from the analysis.

The emissions reduction strategy outlined here relies on changes in user behavior. To account for the limited adoption of emissions reduction strategies we note that 50,000 residential customers obtained home energy audits from DTE Energy as of 2012 [20]. This represents 2.4% of DTE Energy's total customer base (including commercial and industrial customers). For the purposes of an order of magnitude regional calculation we assumed 2.4% of residential customers in the RFCM area would also be open to adopting a LEEM-based emissions reduction approach.

Changes in electricity production as a result of an altered demand profile are neglected in this analysis. With new signals available every five minutes and the dispersed nature of residential users, we expect the real time signal to be nimble enough to account for even very recent changes in electricity production. If adopted on a large scale, LEEM-based changes in the load profile would have the capacity to alter electricity production. Wang et al. [4] observed emissions reductions on the order of 4-5% when modeling emissions optimized spatial load distributions using LEEM in the PJM service area while accounting for this feedback into the electricity production system.

3. Results and Discussion

3.1 Reductions by appliance

Each pollutant was evaluated separately to obtain a timing operation scheme optimized for its particular emission rate. Operating schemes for four of the tested pollutants (SO_2, CO_2e, Hg, and Pb) yielded the same overall emissions profiles over the course of the test year, 2009. This is because fuel types were ranked in the same order for emissions of these four pollutants. Specifically, in the Monroe, Michigan test node, the emission rates ranked from lowest to highest were (1) nuclear/renewable/hydro, (2) natural gas, (3) fuel oil, and (4) coal. For the fifth pollutant, NO_x, the ranking of emission rates was as follows: (1) nuclear/renewable/hydro, (2) natural gas, (3) coal, and (4) fuel oil.

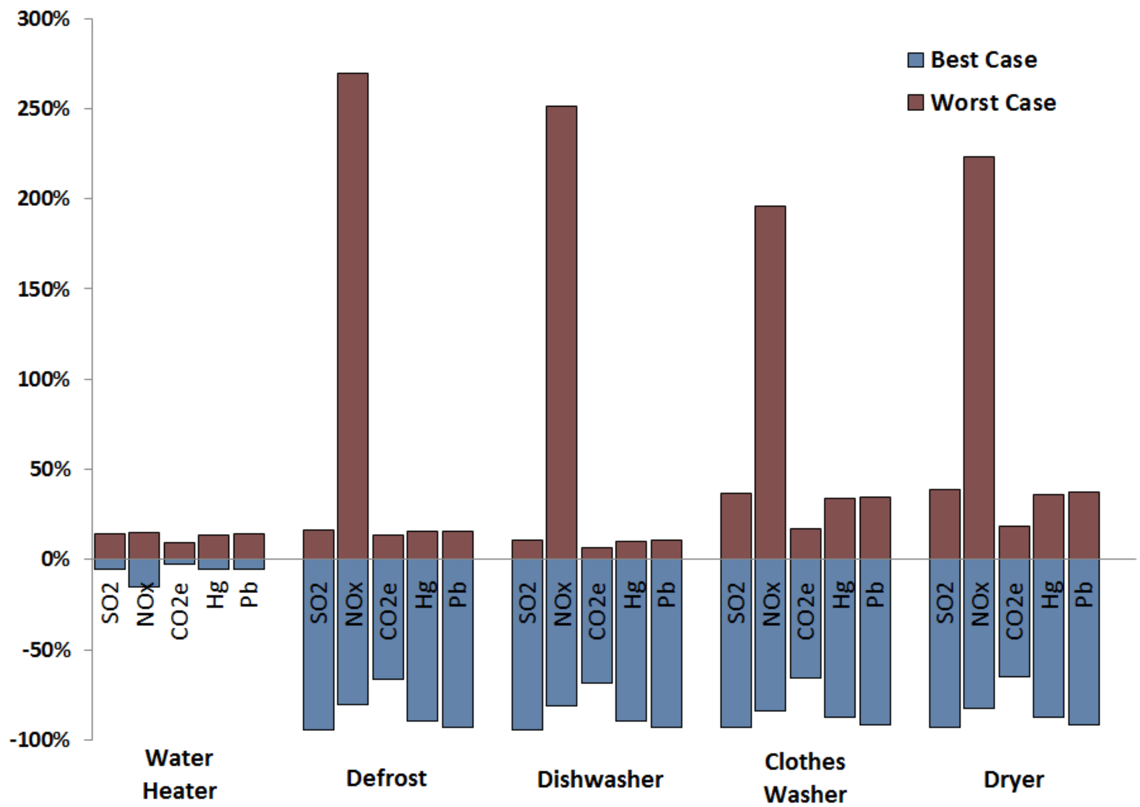

Figure 1. The percent change in emissions from base line for the best and worst case scenarios for a single home. Node in Monroe, MI, 2009.

3.2 Reductions for base case residence

Reductions in emissions between the base case and the best case scenarios are shown in Table 3. A single home's emissions can be reduced by 21 to 35% by following the best case scenario. It should be noted that these emissions reductions require no reduction in actual energy used.

Target Pollutant	SO2	NO x	CO2e	Hg	Pb
SO2	30.0%	21.1%	21.0%	28.4%	29.6%
NO x	27.9%	35.1%	20.5%	26.2%	27.8%
CO2e	30.0%	21.1%	21.0%	28.4%	29.6%
Hg	30.0%	21.1%	21.0%	28.4%	29.6%
Pb	30.0%	21.1%	21.0%	28.4%	29.6%

Table 3. Reductions in emissions between the base case household and the best case scenario. The target pollutant in each scenario is shown in the left hand column. Node in Monroe, MI, 2009.

Improved efficiencies in new equipment may mean that emissions reductions calculated here are an upper limit and actual reductions going forward will not deviate as far from the base case.

3.3 Real-time vs. day-ahead predictions

In comparing RT and DA information, the resulting emission estimates from the five appliances varied between 40 and 88%. This indicates quite a large disparity between "optimized" operating schemes and may indicate that DA information may not be a suitable predictor of future emissions. Table 4 compares the emission factor results from RT and DA hourly-averaged LMP values.

Target Pollutant	Scenario	SO_2	NO_X	CO_2e	Hg	Pb
SO_2	RT Best Case	2.57	1.55	1035	1.49×10^{-5}	2.82×10^{-5}
	DA Best Case	6.58	2.32	1839	3.56×10^{-5}	7.04×10^{-5}
NO_X	RT Best Case	2.87	0.97	1060	1.66×10^{-5}	3.10×10^{-5}
	DA Best Case	6.58	2.32	1839	3.56×10^{-5}	7.04×10^{-5}
CO_2e	RT Best Case	2.57	1.55	1035	1.49×10^{-5}	2.82×10^{-5}
	DA Best Case	6.58	2.32	1839	3.56×10^{-5}	7.04×10^{-5}
Hg	RT Best Case	2.57	1.55	1035	1.49×10^{-5}	2.82×10^{-5}
	DA Best Case	6.58	2.32	1839	3.56×10^{-5}	7.04×10^{-5}
Pb	RT Best Case	2.57	1.55	1035	1.49×10^{-5}	2.82×10^{-5}
	DA Best Case	6.58	2.32	1839	3.56×10^{-5}	7.04×10^{-5}

Table 4. Emission factors (lbs/MWh) for best case scenarios run using real-time and day-ahead information. Node in Monroe, MI, 2009.

3.4 Emissions reductions for the region

Regional emission reductions were calculated using the target pollutant reductions shown in Table 3 and an assumed 2.4% adoption rate by residential users. Regional emissions reductions between the base case and best case scenarios are shown in Table 5. Emissions reductions between 0.01% and 2.3% were observed for each of the five target pollutants. It should be noted that in nearly all cases, reductions in the target pollutant correspond to reductions in the remaining four pollutants, as well, since the emission rates of SO_2, CO_2e, Hg, and Pb share the same fuel rankings and NO_x differs only in its ranking of coal and fuel oil.

Appliance	SO2	NO x	CO2e	Hg	Pb
Water Heater	0.13%	0.01%	0.07%	0.12%	0.13%
Defrost	2.3%	1.6%	1.6%	2.1%	2.2%
Dishwasher	2.3%	1.6%	1.6%	2.2%	2.2%
Clothes washer	2.2%	1.7%	1.6%	2.1%	2.2%
Clothes dryer	2.2%	1.7%	1.6%	2.1%	2.2%
Regional reductions in emissions (lbs/year)	429,000	110,000	87,240,000	2.21	4.53

Table 5. Percent reductions in regional emissions from the base case scenario to the best case scenario. Lead is the target pollutant, 2009.

The Monroe, MI results were compared with a second and third node within RFCM located near Midland, MI and St. Clair, MI, respectively. The average percent difference between Midland and Monroe was 3.7% ± 2.4%. The average percent difference between St. Clair and Monroe was 1.9% ± 2.2%. Both results indicate broad agreement across nodes within in the RFCM region.

3.5 Impact of regional variations in fuel mixes

Analyses were run for three different subregions of eGRID to determine how different generation mixes impact emissions. In addition to RFCM, the other two subregions analyzed were SMRW, which covers most of Illinois and Missouri, and MROW, which covers much of the upper Midwest including Minnesota, Iowa, Nebraska, South Dakota, and North Dakota [9]. SRMW was chosen to reflect a high nuclear/renewable/hydro, high coal, and low natural gas scenario, and MROW was chosen to reflect a high nuclear/renewable/hydro, lower coal scenario. The generation mixes for each of the eGrid subregions used in this comparison are shown in Table 6.

	Percent of total MWh generated				
eGRID Subregion	Nuclear, Renewable, Hydro	Biomass	Coal	Natural Gas	Petroleum Oil
RFCM	15.4%	2.2%	73%	9.5%	0.004%
SRMW	18.9%	0.1%	80%	1.1%	0.003%
MROW	25.4%	2.0%	70%	2.6%	0.023%

Table 6. Generation mix of eGRID subregions: RFCM, SRMW, and MROW. Year 2009 [9].

Our results indicate that modifications in the operating schedule are required to optimize emissions for each of the three regions, but that all three regions can expect significant reductions in emissions by employing a LEEM-based timing strategy. Emissions reductions for all five target pollutants for a single home in the three regions are shown in Figure 2. Emissions reductions are significant across all five pollutants and all three regions. This indicates that adoption of LEEM-based technology in the residential market can have significant impacts on emissions across a variety of geographic areas and fuel mixes.

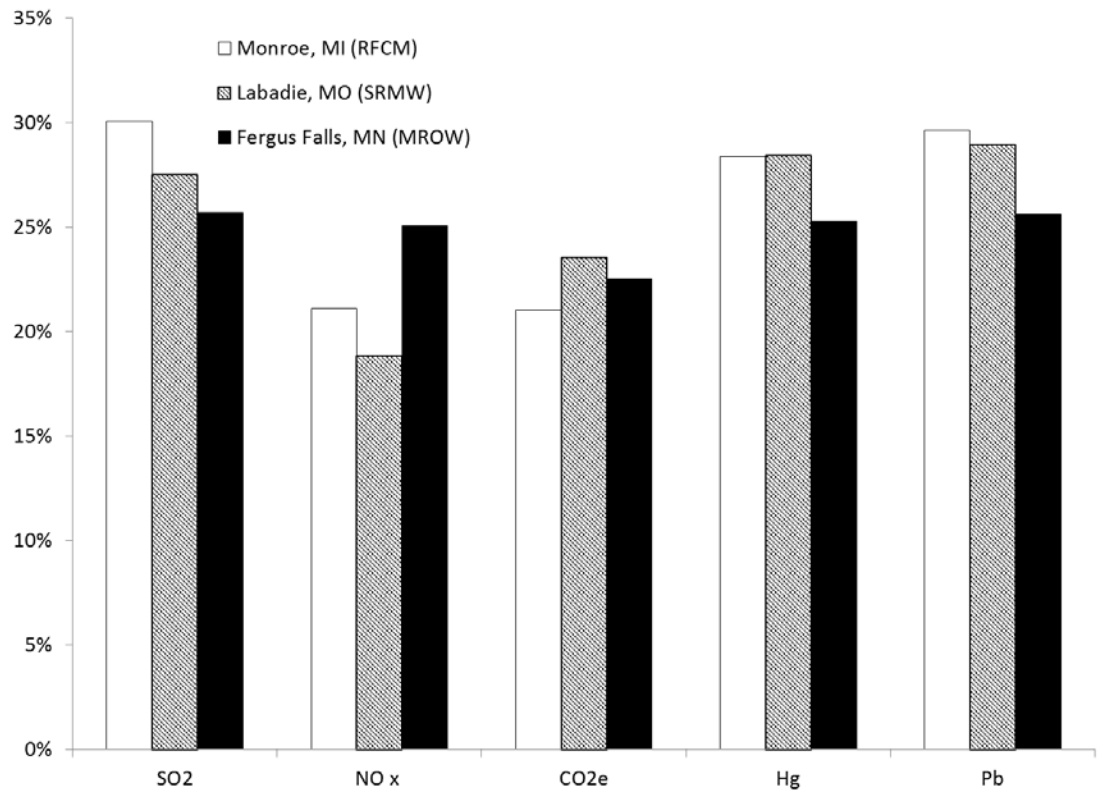

Figure 2. Emissions reductions as a percent between the best case scenario and the base case for subregions RFCM (node: Monroe, MI), SRMW (node: Labadie, MO), and MROW (node: Fergus Falls, MN) for a single home. Year 2009.

It is worth noting that the LEEM approach relies on differences in fuel costs for associated types of generation. Fuel mixes are changing quickly due to increased availability of renewables, increasing domestic supplies of natural gas and crude oil, and retirements of nuclear power plants [21]. Additionally, changing federal emissions standards will have an impact on emission factors for coal-fired power plants [21]. LEEM 2.1 will incorporate updated emission factors and fuel mixes for future studies.

4. Conclusions

LEEM-based emissions reduction strategies can reduce air emissions from electricity in an average residential household in the study area by 21-35% based on optimal timing applied to only five appliances. While the impact of individual appliances varies, in overall pounds of emissions reduced, the emissions reductions are largest for the dishwasher and clothes dryer.

RT and DA information were found to differ 40-88% indicating poor agreement between predictive and actual emissions information on an aggregate level. The LEEM-methodology is currently undergoing refinement as part of ongoing work to define more accurately the parameters of the probability distribution functions used to link pricing information and generation type. Additionally, incorporating LEEM-based technology into automated appliance controls using only RT information or other data streams (e.g. signals provided by ISOs or public utilities) could also be performed therefore eliminating the need for DA information altogether.

On a regional scale, the implications of LEEM-based emissions reductions are significant. For the test area of Michigan, a reduction in emissions of up to 2.3% is achievable from changes in residential consumption patterns alone even with limited adoption. These theoretical emissions reductions are comparable to the 2% energy savings achieved through energy conservation software published by OPower [22].

A comparison with other regions of the Midwest achieved similar reductions (19-29% per household) as the test area of Michigan. This suggests that the widespread adoption of LEEM-based methodologies could be an effective part of regional emissions reduction strategies including state implementation plans (SIPs) for areas not in attainment for criteria pollutants (which include several of the study pollutants – specifically SO_2, NO_2, and Pb). Regional emission reductions achieved via LEEM could also be adopted as part of municipal or regional climate action plans or other greenhouse gas mitigation strategies. The estimated emissions reductions across three different fuel mixes shown here indicates broad applicability of a LEEM-based strategy, and policies that encourage the adoption of LEEM-driven technologies could enhance this impact.

While the project team is currently working to incorporate LEEM-based technologies into automated controllers that will allow for appliances run times to be chosen automatically, in its current form the success of a LEEM-based emissions reduction strategy relies on changes in user behavior. The analysis here assumes a 2.4% adoption rate although it should be noted that energy management behavior modification through electronic resources have had mixed success [23, 24, 25].

To facilitate adoption of the LEEM emissions reduction strategies described above, the project team developed a web accessible (www.herowayne.com) application of LEEM called Home Emissions Read Out (HERO) [26]. HERO determines the user's location either through the user's IP address or manual selection of a location on a map. It then retrieves pricing information from an Independent System Operator (ISO) server, links the locational marginal price to an emission rate, and displays information on the current and projected emission rates. In this way, users have 24 hour-a-day access to immediate pricing and emissions information for electricity generation in their geographic area. The project team is currently optimizing HERO to minimize the barriers to consumer behavior change, and to combine HERO with smart meters, smart appliances, and home-area networks that can detect and control home energy use in real-time. Additionally, the project team is working to refine the LEEM algorithm to accommodate the rapidly changing fuel mix for electricity generators, more accurately identify the most likely prime mover for a particular user, enhance the accuracy of LEEM's fuel price predictions, and improve upon DA calculations. Ultimately the results of this analysis indicate that the widespread distribution and adoption of HERO and other LEEM-based technologies has the potential to significantly reduce emissions from electricity generation.

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