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DSO+T Expanded Study Results

DSO+T Study: Volume 5

October 2022

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U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

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Abstract

The Distribution System Operator with Transactive (DSO+T) study investigates the engineering and economic performance of a transactive energy retail market coordinating a high penetration of customer-side flexible energy assets. The study seeks to answer whether such an implementation is cost effective for customers, recovers sufficient revenue for DSOs, and is equally applicable and beneficial to a range of flexible asset types, renewable generation scenarios, and market assumptions. This report volume provides a detailed set of results for the DSO+T study extending results presented in Volumes 1, 2, and 4. The engineering and economic performance of the transactive energy scheme is presented for two separate flexible asset deployments: flexible loads (space conditioning systems and residential water heaters) and behind-the-meter batteries. The results of each transactive case are compared to a business-as-usual case. These cases are subject to two different renewable generation scenarios, a moderate renewable generation scenario, representative of current levels of renewable generation deployment, and a future high renewables scenario, including the increased deployment of rooftop solar photovoltaic and electric vehicles with smart charging. The transactive coordination scheme is shown to produce effective and stable control and decrease peak loads 9–15%. The resulting annual demand flexibility provides net economic savings of $3.3–5.0B per year for a region the size of Texas. Detailed analysis shows that net benefits were seen for a range of distribution system operator, customer, and flexible asset types. Both participating customer (with transactive flexible assets) and nonparticipating customers (with nonflexible assets) see reductions in annual utility bills and net annual energy expenses.

Summary

This report volume provides a detailed set of results for the Distribution System Operator with Transactive (DSO+T) study extending results presented in Volumes 1, 2, and 4. The DSO+T study investigated the engineering and economic performance of a transactive energy retail market coordinating a high penetration of customer-side flexible energy assets. The presented results were generated using a highly interdisciplinary co-simulation and valuation framework that encompassed the entire electrical delivery system from bulk system generation and transmission, through the distribution system, to the modeling of individual customer buildings and flexible assets. In addition, the economic impact of the transactive scheme on the financial performance of stakeholders was assessed using a rigorous economic valuation methodology. This analysis determined the annualized cash flow of grid operation participants (customers, DSOs, transmission system operator, and ISO) at a level of granularity sufficient to understand the financial benefits and costs incurred by each party.

The engineering and economic performance of the transactive energy scheme was studied for two separate flexible asset deployments: the deployment of flexible loads (HVAC units and residential water heaters) and the deployment of behind-the-meter batteries. The results of each transactive case were compared to a business-as-usual case. These cases were subject to two different renewable generation scenarios, a moderate renewable generation scenario (~15% annual renewable generation), representative of current levels of renewable generation deployment, and a future high renewables scenario (~40%), including the increased deployment of rooftop solar photovoltaic and electric vehicles (EVs). The results of the moderate renewable business-as-usual case were found to be representative of real system performance.

The transactive energy scheme was shown to produce stable and effective coordination of the flexible asset populations resulting in peak system loads decreasing 9-15% and average daily load range decreasing 20-44%. Greater reductions were seen in cases with EVs, that were assumed to have variable charging, due to the additional flexibility they provided. This demand flexibility resulted in economic savings via reduced capacity payments, lower wholesale energy expenses, and deferrals of transmission and distribution investments. After the necessary DSO and customer investments in retail market implementation, advanced metering infrastructure, and flexible asset installation were considered, the net regional benefit was found to be $3.3-5.0B/year. A sensitivity analysis confirmed that these net benefits persisted for a range of market price and implementation cost assumptions.

The granularity of the analysis also allowed the impact of a DSO+T implementation to be assessed for individual DSOs and customers. This analysis showed that such an implementation has net benefits for the broad range of DSO types, customer classes, building types, and flexible asset types studied. For the moderate renewable scenario, the average participating residential customer saw reductions in their annual utility bill of 14-16%. After the customer's annualized expense of installing and operating flexible assets was accounted for, this resulted in an 8-15% reduction in annual energy expenses. Finally, a key finding of this study is that the developed rate design allows non-participants to remain on a fixed-rate tariff and still share in the benefits of the DSO's lower overall cost basis. For the moderate renewable scenario, nonparticipating residential customers saw annual utility bill savings of 10%.

Acknowledgments

This project was supported by the Department of Energy, Office of Electricity, Advanced Grid Research and Develop Program. The authors would like to thank Chris Irwin for his support and contributions to shaping the scope and direction of the DSO+T study.

Acronyms and Abbreviations

AMES	Agent-Based Modeling of Electricity Systems
BAU	business-as-usual
CAISO	California Independent System Operator
CBECS	Commercial Building Energy Consumption Survey
DER	distributed energy resource
DOE	Department of Energy
DSO	distribution system operator
DSO+T	Distribution System Operator with Transactive
EIA	Energy Information Administration
ERCOT	Electricity Reliability Council of Texas
EV	electric vehicle
FL	flexible load
HR	high renewable
HVAC	heating, ventilation, and air conditioning
ISO	independent system operator
LMP	locational marginal price
MR	moderate renewable
PJM	Pennsylvania, Jersey, Maryland Power Pool
PNNL	Pacific Northwest National Laboratory
PV	photovoltaic
RECS	Residential Energy Consumption Survey
SCED	security-constrained economic dispatch
SCUC	security-constrained unit commitment
SOC	state of charge
V1G	Flexible 1-Way Power Flow to Vehicle from Grid
V2G	Flexible 2-Way Power Flow between Vehicle and Grid
WH	water heater

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1.0 Introduction

This report compiles the complete consolidated set of results from the Distribution System Operator with Transactive (DSO+T) study. It includes results previously presented in Volumes 1, 2, and 4 (Reeve et al. 2022a, Reeve et al.2022b, Pratt et al. 2022) in an integrated and expanded form and presents additional analysis (as summarized in Section 1.2). The DSO+T study seeks to simulate a large-scale deployment of flexible assets to demonstrate a feasible method for integrating transactive energy coordination with existing wholesale market operations and assess the economic benefits and costs to grid stakeholders. To achieve this, the study analyzes how a DSO can engage distributed flexible assets, such as responsive heating, air conditioning, and ventilation (HVAC) systems, water heaters, batteries, and electric vehicles (EVs), in the operation of the electric power system by using a coordination strategy based on transactive energy mechanisms.

The DSO+T study compares the engineering and economic performance of transactive cases with business-as-usual (BAU) cases representing the practices of today's distribution utilities with fixed-price rates for all customer classes and no participating flexible assets. This assessment was conducted using a highly integrated co-simulation and valuation framework that encompassed the entire electrical delivery system from bulk system generation and transmission, through the distribution system, to the modeling of individual customer buildings and flexible assets.

The assessment framework has three key elements (as shown in Figure 1): an integrated system model, a transactive coordination and market integration framework, and an economic valuation methodology. The integrated simulation model ensures the physical behavior and constraints of the entire electrical system are modeled including generation dispatch and transmission network constraints, distribution system feeder losses, and distributed energy resource (DER) operation. The transactive coordination framework defines integration of a retail marketplace into an existing competitive day-ahead and real-time wholesale marketplace. Finally, the economic valuation methodology rigorously defines and tracks the flow of value and monetary compensation between market participants. The economic analysis enables the assessment of the overall financial performance of the various transactive study cases for each stakeholder.

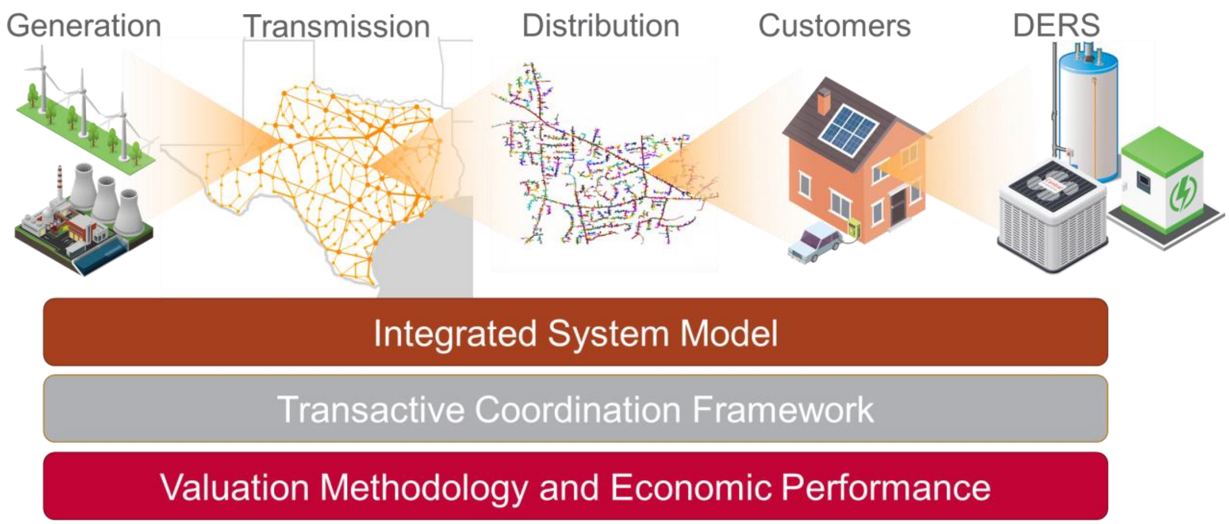


Figure 1. Overview of the DSO+T study breadth and key evaluation elements.

This report is part of a family of reports documenting the DSO+T study. Readers are encouraged to review the study's executive summary[1] and main study report (Volume 1; Reeve et al. 2022a) prior to this report. Volume 2 (Reeve et al. 2022b) describes the instantiation of the large, multiscale annual time-series co-simulation that is the foundation of the analysis, representing a nationally representative generation fleet, transmission system, and distribution system including retail customer building characteristics and controllable and uncontrollable loads and flexible assets. Volume 3 (Widergren et al. 2022) describes the design and integration of the wholesale and retail markets and DER control agents. Finally, Volume 4 (Pratt et al. 2022) describes the process used to assess the value of adopting the DSO+T strategy for all primary stakeholders by comparing the change in various metrics between any two cases of the study.

1.1 Analysis Scenarios

The study examines two cases of transactive flexible asset deployments in each of two different scenarios of renewables penetration. The first deployment case is based on a high participation rate of flexible customer loads (HVAC and water heating). The second is based on a presumption that customer flexible load participation is not ultimately significant and instead batteries become the flexible asset of choice. These flexible asset deployment cases are evaluated across the moderate and high renewable generation scenarios. The intent is to show that transactive energy exchange mechanisms provide stable and economically effective coordination regardless of what types of flexible assets and levels of renewable generation predominate in the future.

At its most basic level, the study consists of parallel analyses of the two scenarios, each with its own BAU case that serves as its baseline. These are illustrated conceptually in Figure 2. The moderate renewable (MR) scenario looks at the combined effect of a DSO engaging a fleet of

[1] The study reports and executive summary are located at: https://www.pnnl.gov/projects/transactive-systems-program/dsot-study

flexible assets deployed at scale and connected with a transactive network when there are moderate levels of renewables in the power system. This level of renewables generation is intended to represent what can may be achieved for the United States as a whole in the absence of federal mandates, based on 2016 levels in California or Texas (17% and 15% of energy generated, respectively). The high renewables (HR) scenario is similar but assumes a high level of annual renewables generation corresponding to aggressive renewables portfolio standards set by a number of states (~40% or more including substantial rooftop PV penetration). The HR scenario also assumes low-cost batteries spur a high level of penetration of EVs, with approximately 30% of households having an EV capable of flexible charging (V1G). Note that the HR scenario does not attempt to achieve even more aggressive goals such as 80% renewables generation or conversion of gas-fueled end uses in buildings to electricity; rather it is intended to examine the relative value of a DSO+T strategy as renewable levels increase.

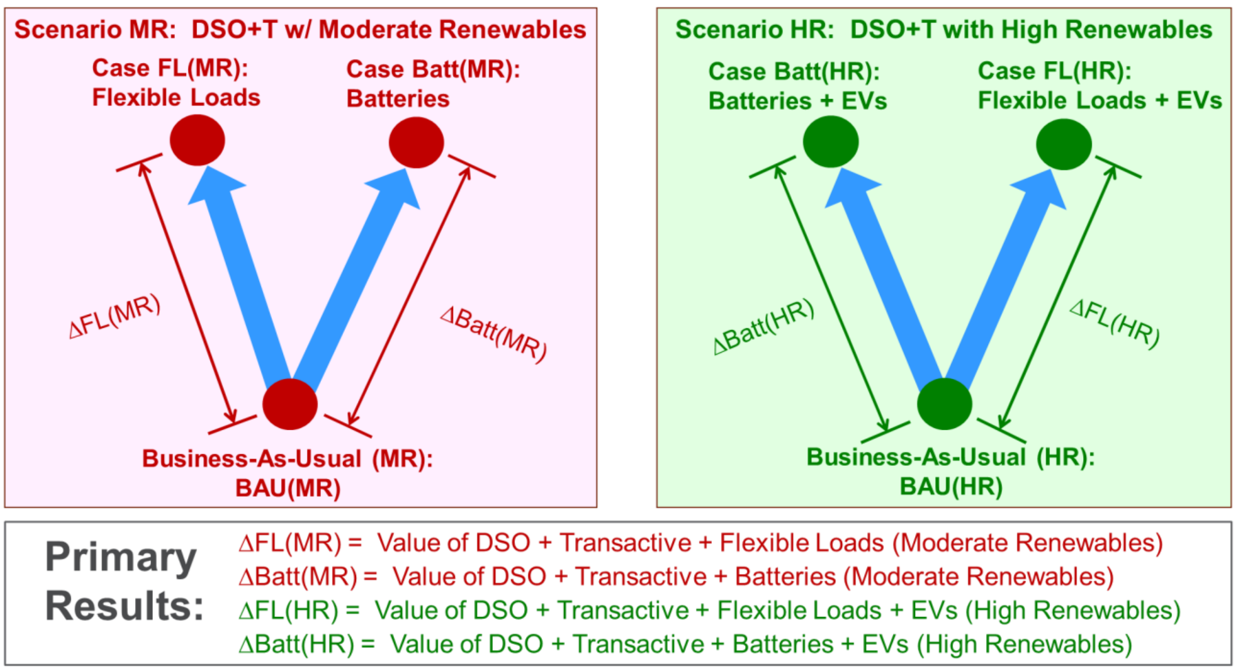


Figure 2. DSO+T study structure and basis of primary results.

Each analysis compares two transactive cases against its respective BAU case:

- The flexible load case (Case FL) assumes a high penetration of flexible loads with substantial customer participation as the primary component of the DER fleet. It also assumes that a majority of residential and commercial customers (~80%) install grid-responsive controls for primary end-use loads such as HVAC and (residential) water heating.
- The battery case (Case Batt) assumes continued breakthroughs in reducing the cost of stationary battery storage and reluctance on the part of most customers to provide flexibility from their loads will result in distributed storage dominating the DER fleet. A comparable amount of distributed battery storage will be assumed, sufficient to provide about the same approximate size resource as the fleet of flexible loads in the flexible load case. This equates to approximately 40% of residential and commercial buildings having average battery storage of 14.2 kWh each (a total capacity of 21.3 GW).

A summary of flexible asset deployment and participation rates for the various cases and scenarios is shown in Table 1. This study limits EV deployment to only residential customers due to data and modeling constraints. In addition, only residential water heaters are modeled and assumed to participate.

Note that the study simulates the system under 2016 conditions and, where possible, data are used from 2016 for key assumptions and comparisons. The BAU cases aim to represent current distribution utilities' infrastructure, operation, and cost structure. The simulation includes the integrated analysis of the wholesale generation fleet, transmission and distribution systems, and end-use loads. Transmission and distribution system capacity constraints and their impact of system prices are also included. The Electric Reliability Council of Texas (ERCOT) region was selected as a nationally representative system to serve as the basis of the DSO+T simulation as it has a generation mix with significant amounts of wind, is summer peaking, is served by an independent system operator's wholesale market, and is of tractable size with no synchronous interconnections. Weather profiles for 2016 were used for the various regions to allow the comparison of calculated loads to actual ERCOT data. Finally, the DSO+T study results were calculated for both a 200-bus model (simulating 40 DSOs and approximately 64,000 representative customer buildings) and a leaner 8-bus model (simulating 8 DSOs and ~12,000 representative buildings). Unless otherwise stated the results in this report are for the 200-bus model. Full details of the system definition are provided in Volume 2 (Reeve 2022b).

Table 1. Summary of flexible asset deployment and participation rates by analysis case.

Asset Deployment and Participation Rates	Moderate Renewables			High Renewables		
	BAU	Flex	Battery	BAU	Flex	Battery
Annual renewable generation	15%	15%	15%	42%	42%	42%
Customers with HVAC	97%	97%	97%	97%	97%	97%
Fraction of HVAC participating	0%	82%	0%	0%	82%	0%
Residential customers with water heaters	61%	61%	61%	61%	61%	61%
Fraction of water heaters participating	0%	77%	0%	0%	77%	0%
Residential customers with EVs	0%	0%	0%	33%	33%	33%
Fraction of EVs participating	0%	0%	0%	0%	92%	92%
Customers with batteries	0%	0%	40%	0%	0%	40%
Fraction of batteries participating	0%	0%	100%	0%	0%	100%
Customers with rooftop solar	0%	0%	0%	31%	31%	31%
Total fraction of customers participating	0%	81%	40%	0%	81%	58%

1.2 Report Structure

The remainder of the report is organized as follows. Section 2.0 presents the business-as-usual results for the MR and HR scenarios that serve as the datum for the analysis. This includes Section 2.3 which includes a comparison between the 200- and 8- bus modeling results showing good agreement between the two modeling resolutions. Section 3.0 discusses the impact of transactive operation on system loads, market prices, and overall economics. This section includes a review of the impact on the dispatch of the generation fleet (Section 3.1.2) which was not covered in Volume 1. Section 4.0 presents the results from the customer population perspective. This includes additional results of the business-as-usual customer energy consumption, peak loads, and annual energy costs. The impact of participating in a transactive tariff is then presented with additional detail on the change in monthly bills (Section 4.2.2), the impact on customer metrics as a function of DER ownership, and an investigation of the small fraction of the population that may pay more under a transactive tariff (Section 4.2.4). Section 5.0 provides additional detail on the savings by DSO type. Section 6.0 provides overall discussion of the study results and areas that warrant further investigation and improved capability. Section 7.0 concludes the report.

2.0 Business-as-Usual System Performance

This section describes the performance of the BAU cases for the moderate and high renewable scenarios. These results comprise system load profiles, generation dispatch schedules, and resulting wholesale energy prices and economic performance. They provide the baseline to which the transactive cases are compared. In Section 2.1, the MR BAU case is compared to data from actual ISOs to show the representativeness of the simulation to actual real-world system performance. The performance of the HR BAU case (in comparison to the MR BAU case) is presented in Section 2.2. Finally, the effect of simulation scale and resolution on these results is presented in Section 2.3.

2.1 Moderate Renewable Scenario

This section presents the system loads, bulk generation dispatch, transmission system operation, wholesale energy prices, and system economic costs for the MR BAU case. Figure 3 provides a summary of the annual average generation by fuel type and end loads by customer class and end-use type for the 8-node simulation model of the MR BAU case.

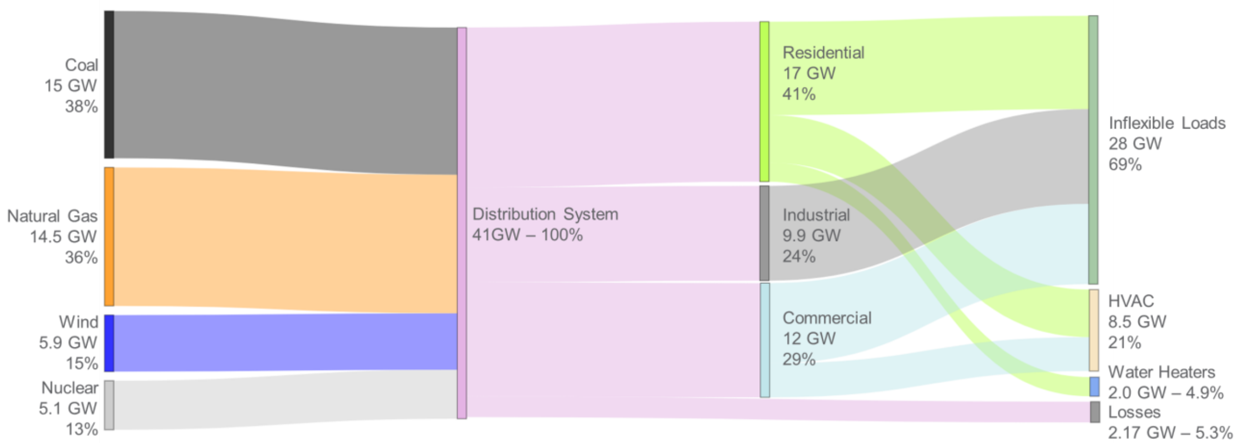


Figure 3. Annual average power by generation source, customer type, and end-use load for the MR BAU case (8-bus model).

2.1.1 System Loads

This section summarizes the system load results by end-use, customer class and building type. It also compares the resulting daily and seasonal load patterns to actual 2016 ERCOT data.

2.1.1.1 System Load by End-Use

The system loads included in this study are comprised of water heater (WH) loads, HVAC loads, plug loads (including all other non-price-responsive residential and commercial loads), and industrial loads. Industrial loads are assumed to be constant and are assumed to be non-price responsive. Example load profiles (by end-use load type) are shown in Figure 4 for the weeks with maximum and minimum actual 2016 ERCOT loads. The simulation's overall system load compares well with the actual ERCOT peak load (summer) week but overpredicts the reduction in load at night. During the minimum load (spring) week the load shape is trend-wise accurate but overpredicted. The plug and miscellaneous electrical loads are based on predefined schedules with weekday and weekend dependence. The water heater load shape is primarily driven by assumed usage (water draw) profiles. Finally, the HVAC load is driven by ambient weather conditions and occupancy schedules. Annual end load consumption is shown in Table 2. HVAC accounted for 24% of total annualized distribution system load (excluding losses) versus CBECS/RECS-based estimates of 29.6%, and residential water heating contributed 5.7% versus RECS-based estimates of 5.2%. (Note that the CBECS- and RECS-based values are based on South-West Central Census Region data that is then corrected for building class contributions. For example, water heating is estimated by RECS to account for 12% of residential load in the region. Given that residential customers represent 43% of ERCOT load we would expect water heaters to present 5.2% of load not including distribution losses.)

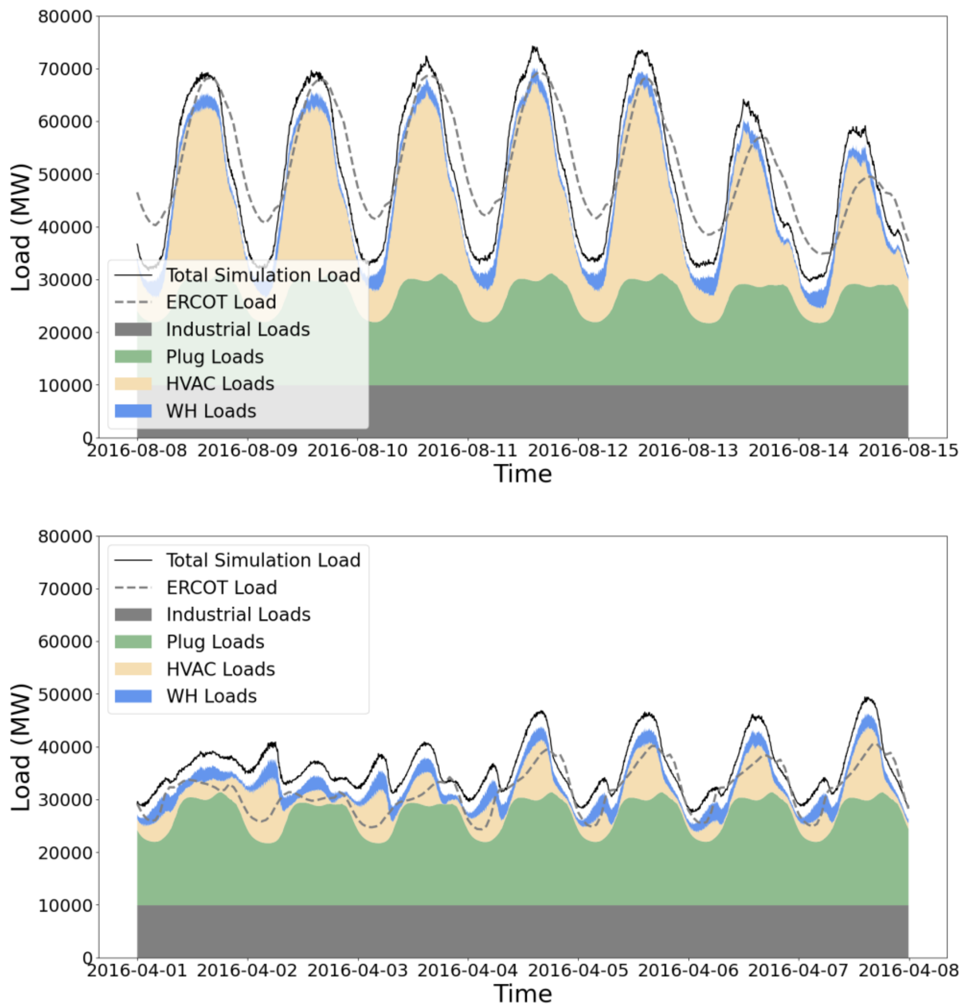


Figure 4. System load contributions by end use for week of annual peak (top) and minimum (bottom) load. Total simulation load (solid line) is shown in comparison to actual load experienced in ERCOT (dotted line).

Table 2: Summary of simulated end-use device numbers and loads.

	Simulated		Scaled		Building Load	
End-Use Load	Number	%	Number	%	Load (MW-hr)	%
HVAC	73,704	66.8%	11,627,729	66.4%	64,605,889	23.6%
Water Heaters	36,624	33.2%	5,871,794	33.6%	15,507,344	5.7%
Plug Loads	-	-	-	-	130,873,225	47.7%
Industrial Loads	-	-	-	-	63,257,981	23.1%
Total	110,328	100%	17,499,523	100%	274,244,439	100%

2.1.1.2 System Load by Customer Class and Building Type

Figure 5 shows similar system load profile examples but broken out by customer class and building type. Table 3 shows that residential and commercial buildings loads compared well to ERCOT utility data in terms of both overall contributions and the average value per building. While utility data were not available for load factor (the ratio of building average load to peak load), the values are comparable (but higher) than those reported by (New et al. 2019) based on >170,000 buildings in Tennessee, with load factors of 0.23 versus 0.16 for residential buildings and 0.37 versus 0.27 for commercial buildings.

Table 4 shows the number, proportion, and load by building type in the simulation before and after the weighting factors are applied. Residential buildings account for >90% of the customer buildings and >60% of the load (excluding industrial load). This is dominated by single-family homes (70% of the buildings and 50% of the load). Significantly more diversity in building type is seen in the commercial customers. The most prominent commercial building types are office buildings and big-box retail buildings each representing 8-9% of non-industrial load.

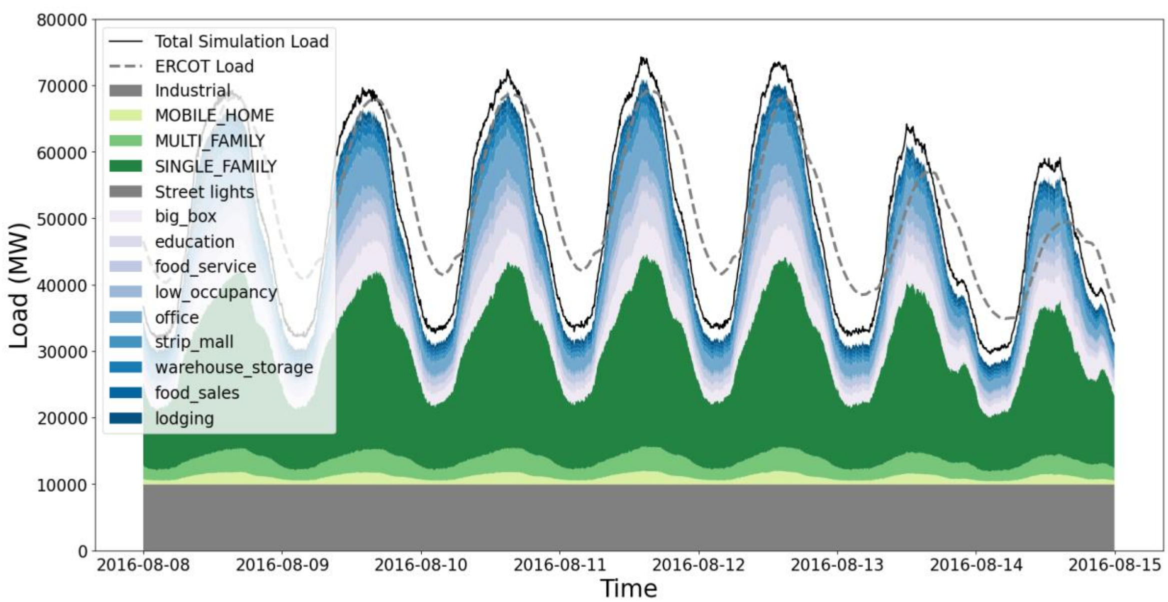


Figure 5. System demand by customer class (green for residential, blue for commercial, and grey for industrial) and building type for the week of peak load.

Table 3. Comparison of loads by customer class.

Statistic	Residential Simulation	Residential Actual	Residential Diff (%)	Commercial Simulation	Commercial Actual	Commercial Diff (%)
Class load (%)	45.2%	43.3%	4.4%	30.7%	31.2%	1.5%
Average load per Customer (kW)	1.73	1.59	8.9%	9.30	9.00	3.5%

Table 4. Summary of simulated residential and commercial customer loads by building type and customer class.

		Simulated		Scaled		Building Load	
Customer Class	Building Type	Number	%	Number	%	Load (MW-hr)	%
Residential	Single-Family	44,019	69.1%	7,496,214	70.7%	107,514,838	50.0%
	Mobile Home	4,485	7.0%	438,043	4.1%	5,464,985	2.5%
	Multifamily	9,949	15.6%	2,133,030	20.1%	17,992,707	8.4%
	Total	58,453	92%	10,067,287	95%	130,972,530	60.9%
Commercial	Office	1,074	1.7%	117,416	1.1%	16,509,851	7.7%
	Warehouse & Storage	898	1.4%	93,846	0.9%	8,173,540	3.8%
	Big Box	1,246	2.0%	128,967	1.2%	18,693,237	8.7%
	Strip Mall	110	0.2%	12,520	0.1%	6,996,139	3.3%
	Education	395	0.6%	46,529	0.4%	11,184,126	5.2%
	Food Service	317	0.5%	28,821	0.3%	8,087,731	3.8%
	Food Sales	193	0.3%	17,770	0.2%	5,149,110	2.4%
	Lodging	152	0.2%	11,568	0.1%	4,241,945	2.0%
	Healthcare Inpatient	1	0.0%	201	0.0%	228,624	0.1%
	Low Occupancy	887	1.4%	82,450	0.8%	4,994,222	2.3%
	Total	5,273	8%	540,088	5%	84,258,525	39.1%
Total		63,726	-	10,607,375	-	215,231,055	-

2.1.1.3 Annual System Load Results

Summaries of load and daily change in load by month for the 200-bus model are provided in Figure 6 and an overall summary is provided in Table 5. This confirms that while the overall average load is accurately captured (within ~5% percent), the daily variation in load is overpredicted (on average by ~37%), and the minimum total load is overpredicted by ~10%.

As noted above, the load simulation results have two main inaccuracies: the over-prediction of the range (swing) of diurnal loads (especially in the summer) and the over-prediction of electric loads in the winter heating season. Work by Hale et al. (2018) also overpredicted the daily swing. This suggests that the use of a higher fidelity simulation tool (for example, EnergyPlus) or more detailed building survey data (for example, ComStock and ResStock databases) would be unlikely to resolve this issue. The overprediction in the daily change in building load could be due to overly optimistic assumptions about the nighttime reduction of miscellaneous electric loads and building thermostat schedules. Lower diurnal variation of each of these would improve the agreement with actual loads. In addition, increased nighttime HVAC operation could be explained by a desire to address latent cooling rather than sensible cooling objectives. In addition, there are a number of building parameters that do not have well-characterized probability distributions in the literature that could contribute to this issue. These include infiltration and natural ventilation (window opening rates), shading and its impact on solar loads, and accurate distributions of buildings' thermal mass and the heat transfer coefficient from the interior air to building thermal mass.

The overprediction of winter loads likely arises from inaccuracies in estimating the proportion of homes with gas heat. Calibration methods were not used in this study to tune input parameters and improve accuracy but could be in the future. For example, changing the proportion of homes with gas heat from ~40% to ~60% reduced the average load error to less than 5% and minimum system load error to less than 10%. It also improved the average residential load error to 0.3%. However, this resulted in a substantial reduction in the load contribution from electric water heaters and HVAC, increasing the risk that their contribution to load flexibility would be under-represented. Auto-calibration techniques could result in improved load shape accuracy at the risk of substantial losses in the representativeness of contributions of end loads and customer classes. Prior work (Fuller n.d.) has shown that detailed calibration of GridLAB-D building models with customer data can reduce load shape inaccuracies but still reported a >14% mean average percentage error.

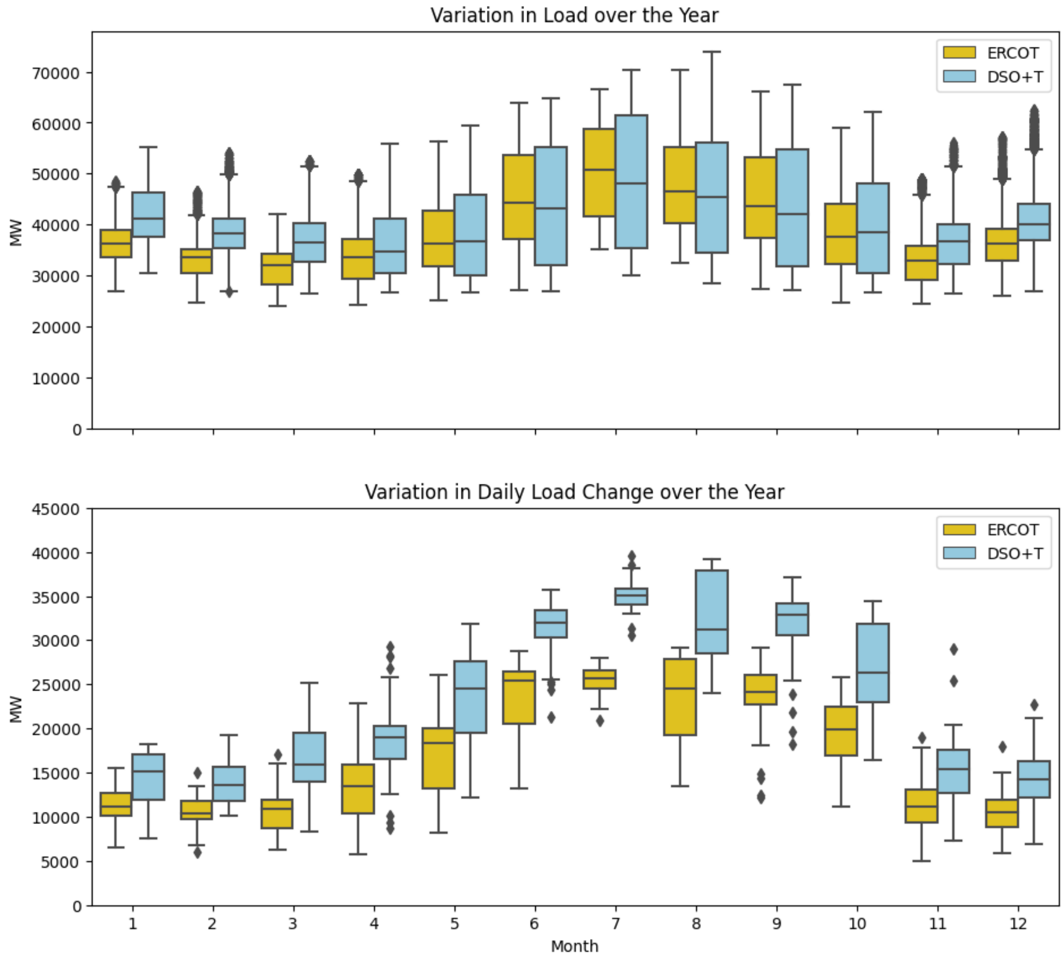


Figure 6. Comparison of system total load (top) and diurnal range in total load (bottom) between the 200-bus MR BAU simulation (DSO+T) and actual 2016 data (ERCOT).

Table 5. Comparison of the 200-bus MR BAU simulated grid load with actual 2016 ERCOT data.

System Load (MW)	DSO+T	ERCOT	% Diff
Average	40,998	39,191	4.6%
Max	73,938	70,359	5.1%
Min	26,545	24,098	10.2%
Average daily range	23,049	16,795	37.2%
Max daily range	39,588	29,146	35.8%
Min daily range	6,861	5,036	36.2%

2.1.2 Bulk System Generation Dispatch Results

The load profiles presented in the preceding section provided the basis for the required bulk system generation dispatch. The open-source AMES tool (AMES n.d.; Li and Tesfatsion 2009; Tesfatsion and Battula 2020), was used to simulate the wholesale market operations. Given market bids and reliability operating constraints, AMES determined the day-ahead scheduling of generators and their real-time dispatch by solving the day-ahead security-constrained unit commitment (SCUC), the real-time security-constrained economic dispatch (SCED), and calculating the locational marginal prices (LMPs) for each market cycle. The DSO+T real-time generator dispatch and actual ERCOT values are compared in Figure 7 for the MR BAU case. The overall generation dispatch trends and resulting fuel mix suggest that the simulation is representative. In addition, the dispatch of nuclear, coal, and gas generators is trend-wise accurate.

The simulation appears to enact more aggressive ramping of the coal fleet than was observed in the ERCOT case. This may be due to larger diurnal load changes in the simulation or the lack of a soft constraint in AMES to minimize ramping on these generators. It should be noted that, since the wind generation profiles are stochastically generated and not based on 2016 data, a direct comparison of the simulated and actual 2016 wind profiles is not appropriate. The annual generation capacity and production values are summarized in Table 6. This indicates that the simulation dispatches more coal generation (at the expense of gas) than would be expected based on the 2016 ERCOT system data. The overall level of natural gas generation is representative of the nation as whole.

Table 6. Summary of system capacity and production by generator type for the MR and HR scenarios versus ERCOT and the U.S. in 2016.

	Capacity				Generation			
Fuel	ERCOT	U.S.	MR	HR	ERCOT	U.S.	MR	HR
Nuclear	5%	9%	5%	3%	12%	20%	13%	11%
Coal	20%	25%	22%	15%	29%	30%	38%	26%
Natural gas	58%	41%	56%	37%	44%	34%	35%	23%
Wind	15%	7%	17%	22%	15%	6%	14%	26%
Solar (utility scale)	1.0%	2%	-	10%	0.2%	1.0%	-	6%
Solar (distributed)	-	1%	-	13%	-	-	-	8%
Other	5%	15%	5%	3%	-	9%	13%	11%

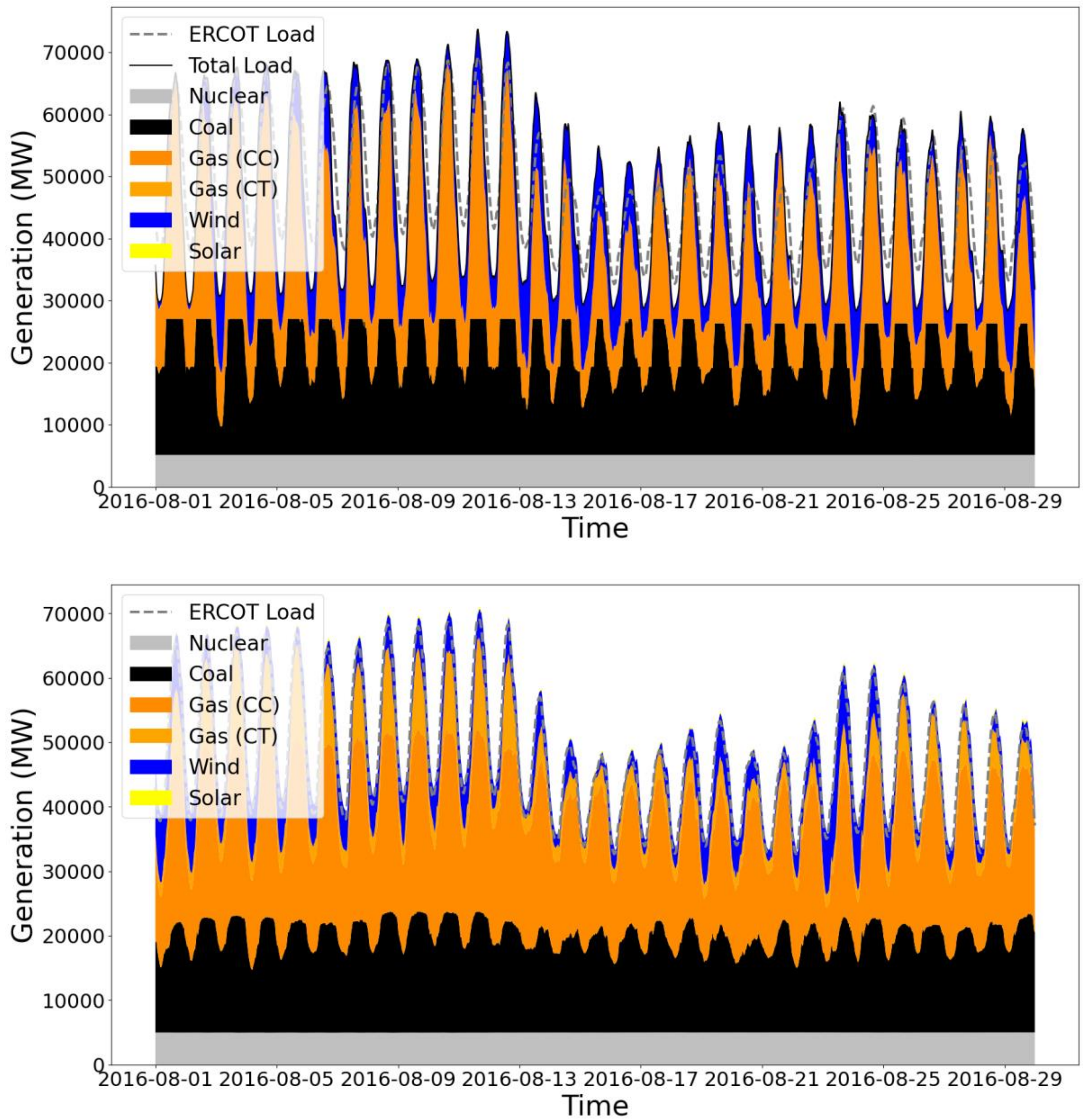


Figure 7. Comparison of AMES real-time generation dispatch for the MR scenario (top) versus actual ERCOT dispatch (bottom) for August 2016.

2.1.3 Transmission System Results

The scheduling and dispatch of generation presented in the preceding section can be constrained by transmission system congestion particularly during periods of peak load. This section provides illustrative results of the geographic distribution of the system loads, generation dispatch, resulting transmission system utilization and, ultimately, resulting market prices. Results are shown for the system peak generation (73.4 GW) that occurs at ~4 p.m. on August 12. Figure 8 shows the geographic distribution of the peak load and the resulting transmission system loading. The contour plot shows the load for each bus and highlights that over 50% of the system load occurs on just 5 buses, representing population centers in the north and east of Texas. In comparison, the more rural western Texas region has much lower loads. The fractional utilization of the transmission lines is also illustrated using a color gradient, with fully utilized lines (that is, a normalized line capacity utilization of 1.0) shown as red. This shows that there is higher transmission line utilization and congestion in lines serving and adjacent to the major load centers.

Figure 9 and Figure 10 show similar plots for the geographic distribution of thermal generation capacity and resulting dispatch. There is significant generation capacity adjacent to the major load centers and during the system peak load these generators see a high level of dispatch. (Note that not all system nodes have dispatchable generation and therefore may not be able to have generation dispatch fractions greater than zero). Finally, Figure 11 shows the resulting variation in real-time prices during the system peak. The LMP distribution is dominated by a single node (DSO 127) whose real-time LMP has reached the market cap of $2,000/MW-hr for several hours during the afternoon. Figure 12 shows real-time LMPs in the transmission system later in the day (5 p.m.) when lower loads result in fewer transmission constraints and a return to typical price ranges ($30-50/MW-hr).

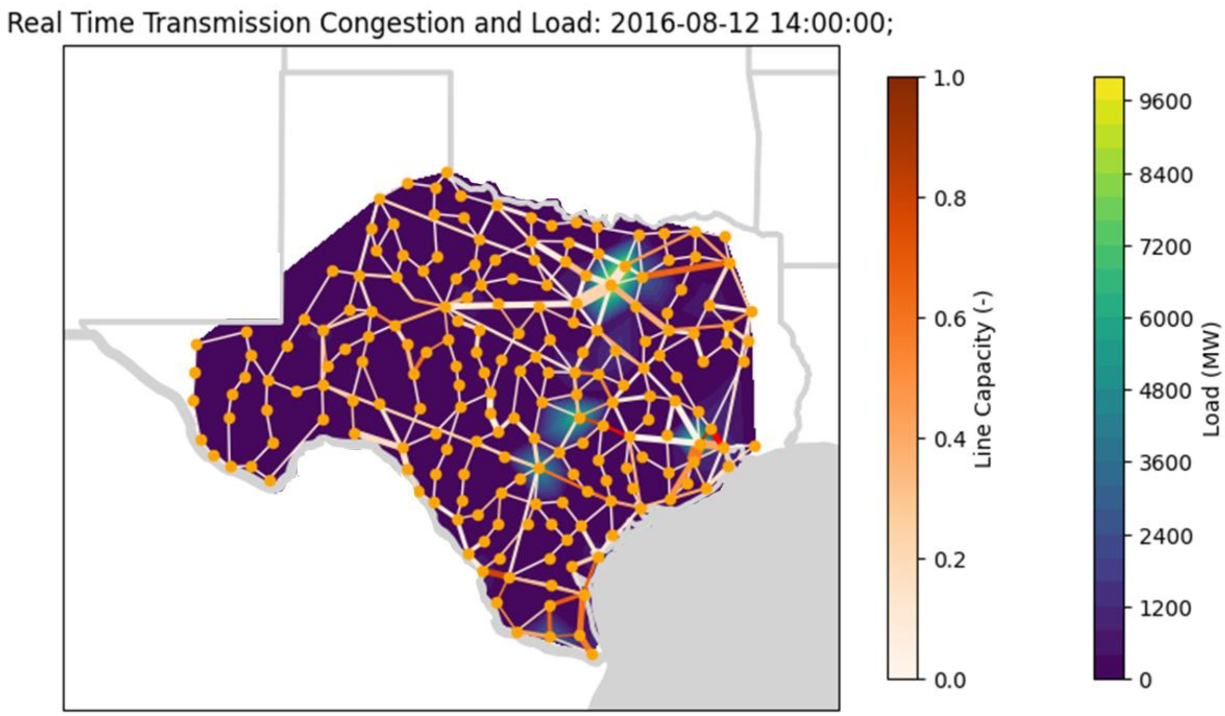


Figure 8. Geographic distribution of real-time load in the DSO+T system model during the system peak load.

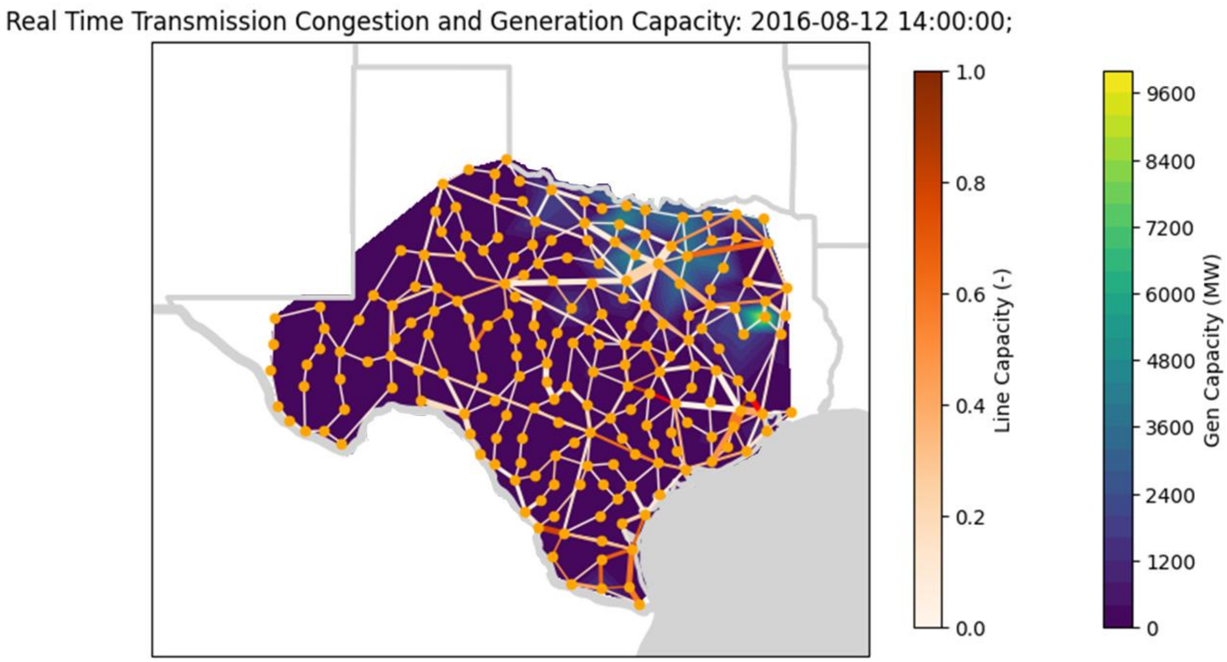


Figure 9. Geographic distribution of generation capacity in the DSO+T system model during the system peak load.

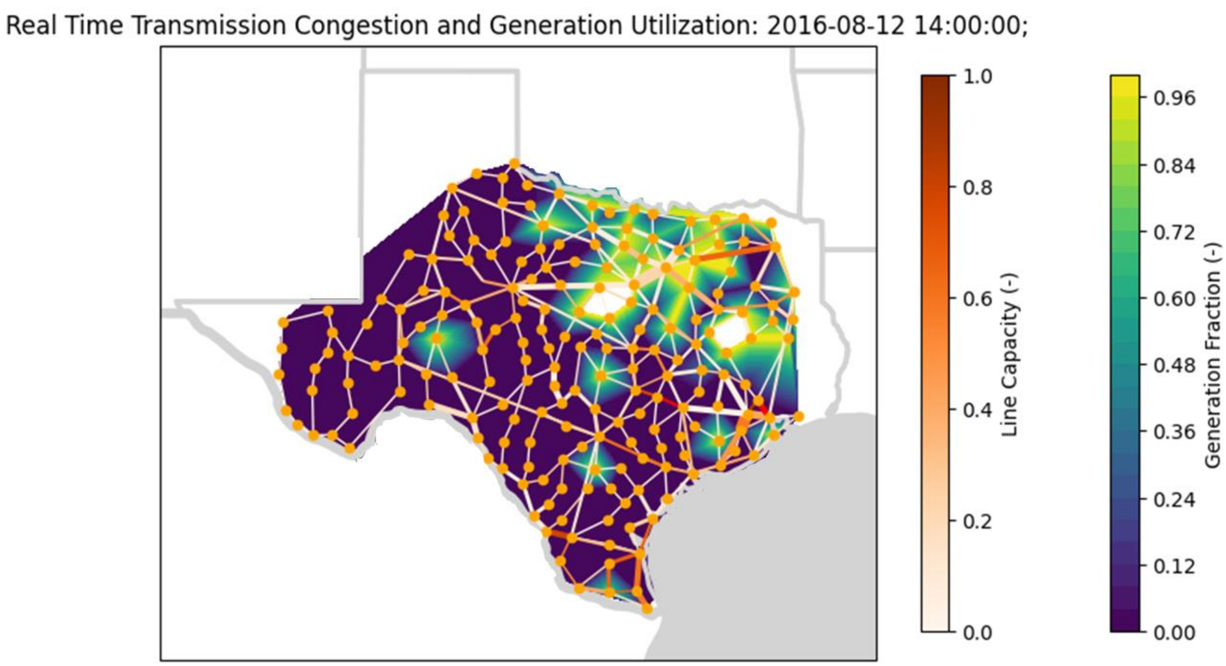


Figure 10. Geographic distribution of dispatchable generation utilization in the DSO+T system model during the system peak load.

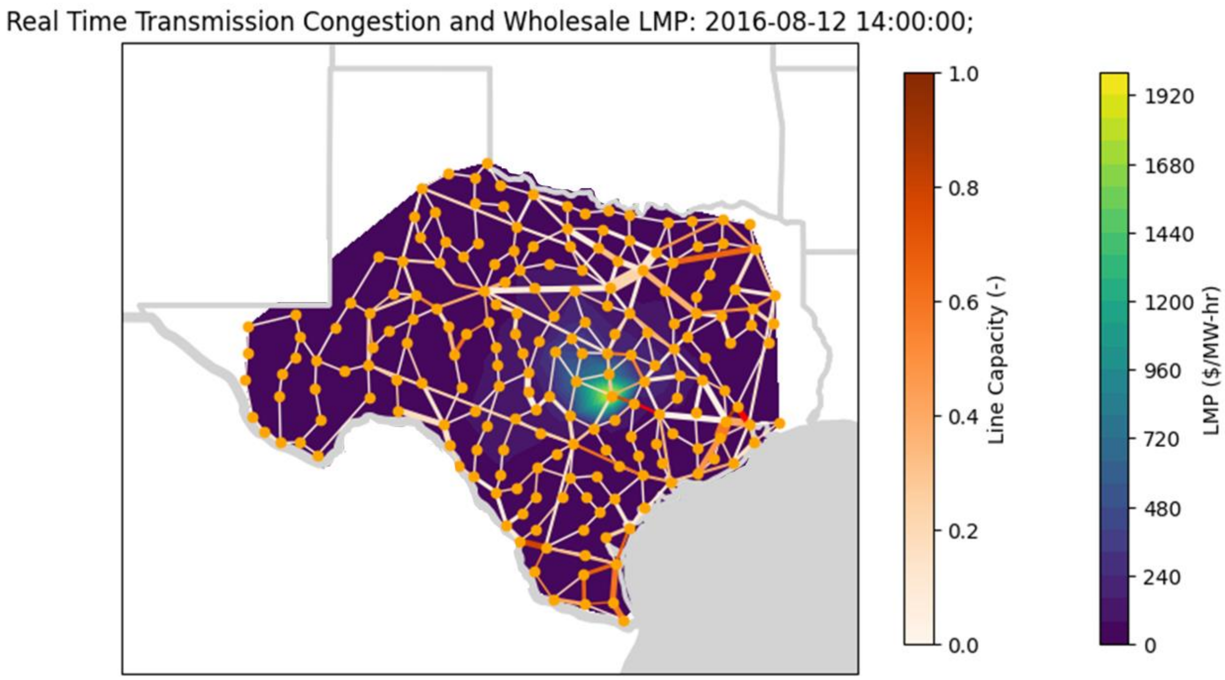


Figure 11. Geographic distribution of the resulting real-time LMPs in the DSO+T system model during the system peak load.

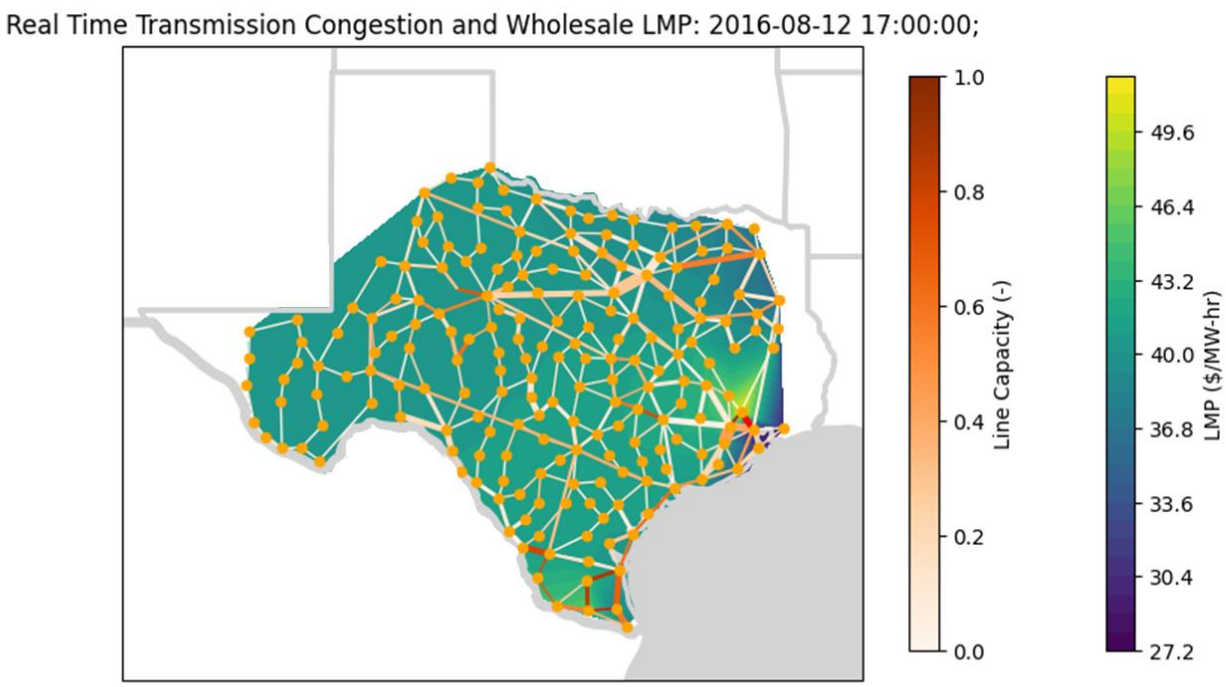


Figure 12. Geographic distribution of real-time LMPs in the DSO+T system model at 5 p.m. on August 12, 2016.

2.1.4 Wholesale Market Price Results

The SCUC and SCED processes used by AMES to determine thermal generation scheduling and dispatch also influence the calculation of the LMP at each node within the transmission system. Figure 13 shows a time history of day-ahead and real-time LMPs at a representative transmission node during the summer peak compared with 2016 ERCOT data. This illustrates that the simulation captures the overall daily trends and variation with system load. The simulation does not sufficiently capture, however, the frequency of large, rare price spikes.

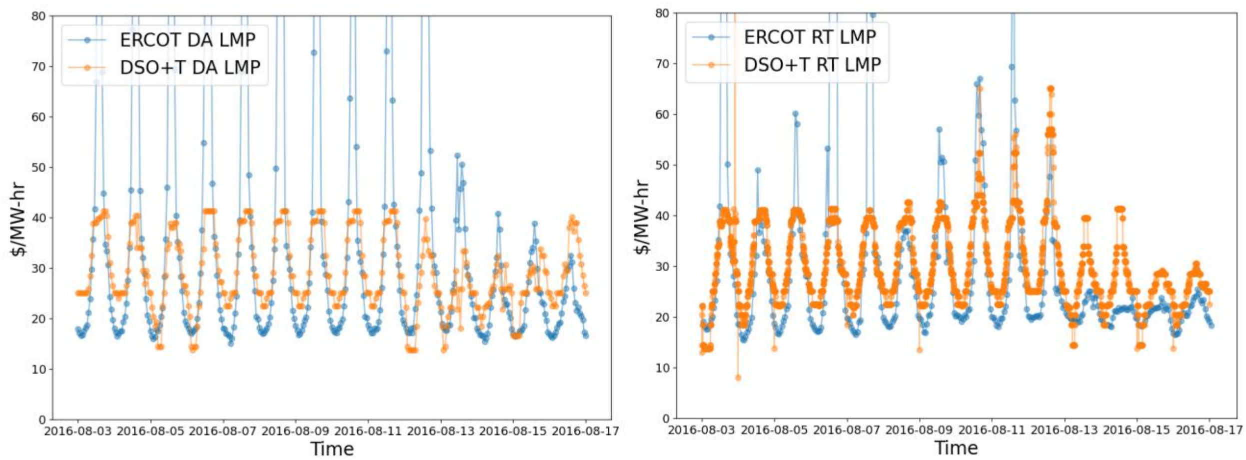


Figure 13. Comparison of DSO+T and ERCOT day-ahead (left) and real-time (right) prices in two weeks of August 2016.

To ensure that the market prices generated by the simulation were also representative of other regions in the country, the annual DSO+T results were also compared to data from the PJM and CAISO markets. 2016 data was used for ERCOT and PJM and, due to availability, 2017 data was used for CAISO. In addition, since these prices vary by location, zones had to be selected in each region to compare data. For ERCOT, the Houston zone data is presented, for PJM the PJM node is presented, and for CAISO the SNTHLNE_6_N001 node is shown. For the simulation, results from DSO 3 are shown for the 8-node case.

Figure 14 through Figure 17 show detailed comparisons of day-ahead and real-time prices throughout the year. They also show summaries of the daily range in price. (The daily range in price is the maximum price for the day minus the minimum price.) The box and whisker plots show that the simulation accurately captures average LMPs that are representative of typical wholesale markets. The quantity versus duration curve for the day-ahead price (Figure 16, left) emphasizes this, showing that the study prices are similar in magnitude to PJM and are bounded by CAISO (which experienced high prices at the zone in question) and ERCOT (which had lower prices). However, the simulation does not capture the ‘tails’ of the price distribution seen in real market operation, particularly in the shoulder seasons. As can be seen in Figure 14 (bottom) and Figure 16 (left) the DSO+T market model consistently underpredicts the daily range in day-ahead prices and overall price volatility seen in national electricity markets. For example, ERCOT and CAISO have day-ahead prices below $10/MWh approximately 5% of the time, and all three comparison markets have prices above $50/MWh approximately 5% of the time. The end result is that the DSO+T simulation underpredicts median daily variation in day-head prices by 32-70% when compared to the three regional markets. Since this variation in day-head price drives DER bidding strategy and economic benefits, this area warrants improvement in future market modeling. Similar trends are seen for real-time prices as well.

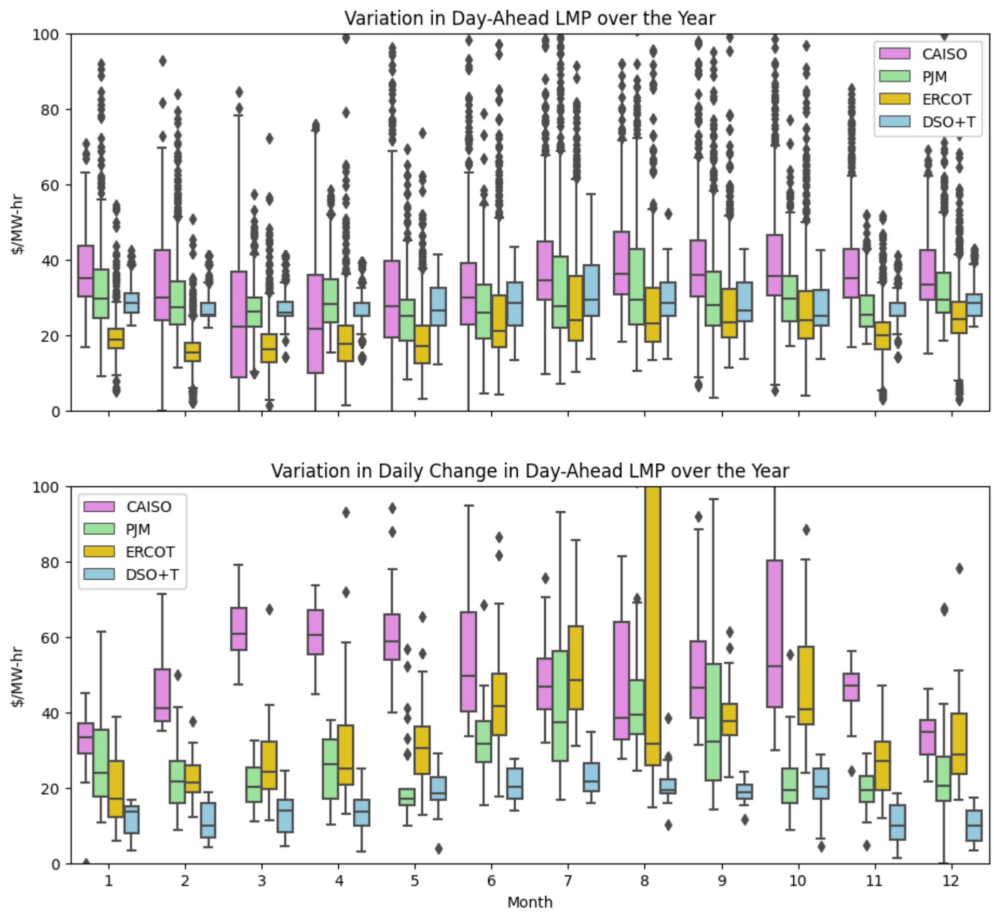


Figure 14. Comparison of day-ahead market prices (top) and daily range in day-ahead market price (bottom) for various regions and the simulation.

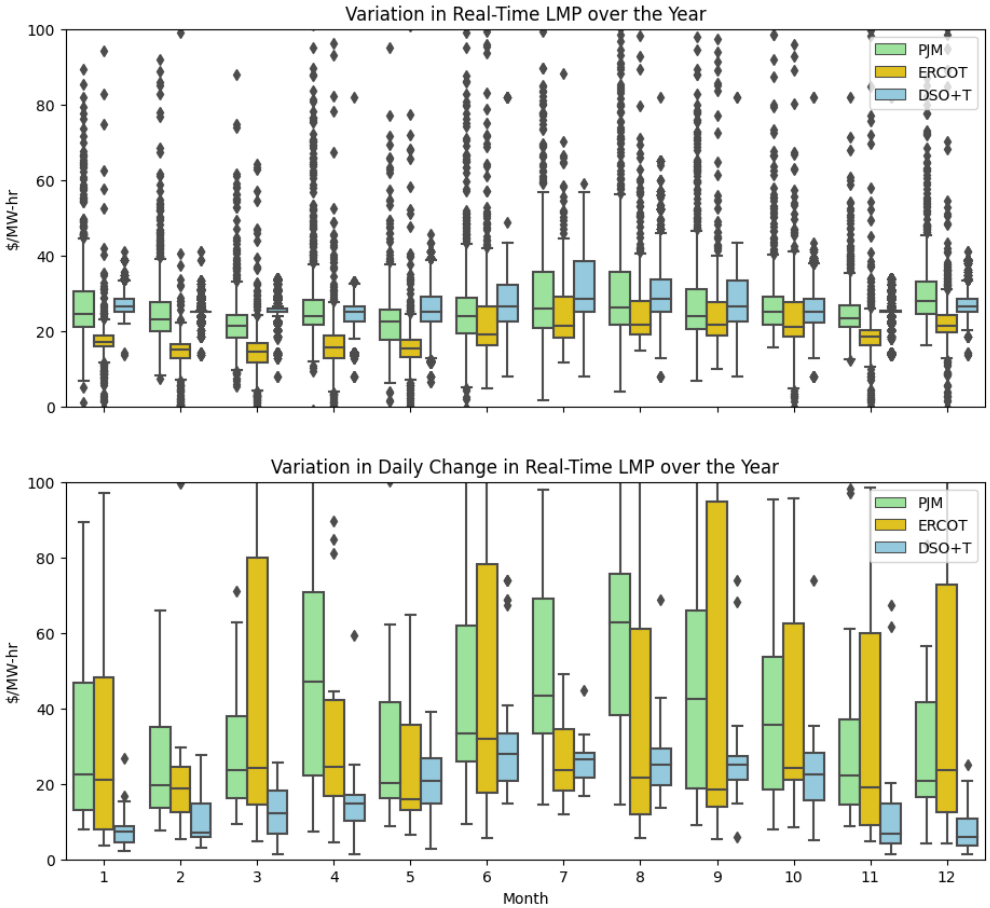


Figure 15. Comparison of real-time market prices (top) and daily range in real-time market price (bottom) for various regions and the simulation.

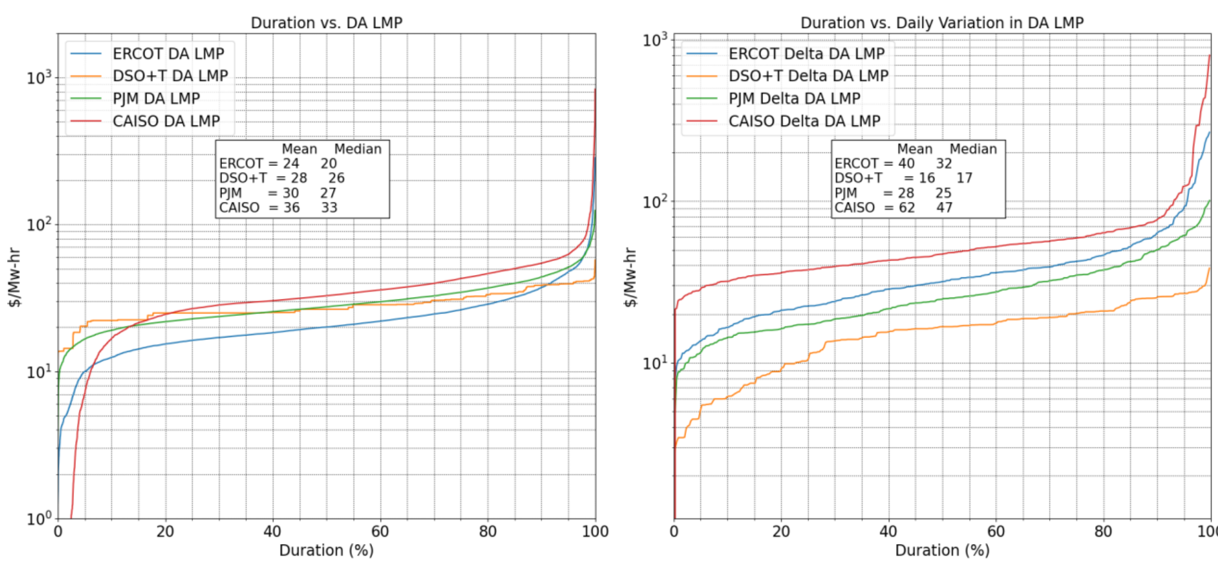


Figure 16. Duration vs. quantity curves for day-ahead market prices (left) and daily range in day-ahead market price (right) for various regions and the simulation.

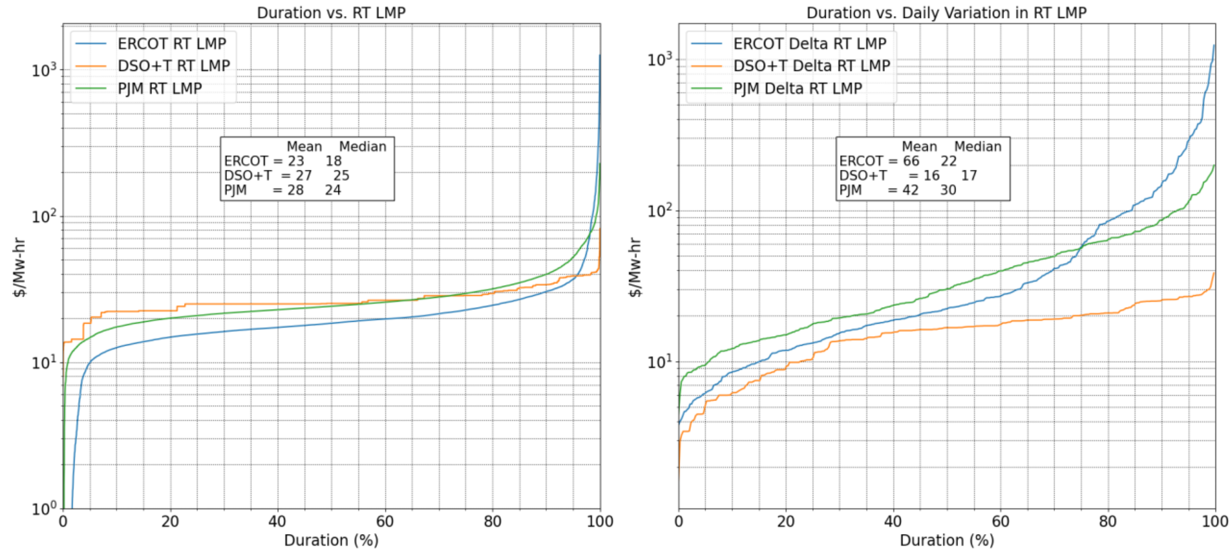


Figure 17. Duration vs. quantity curves for real-time market prices (left) and daily range in real-time market price (right) for various regions and the simulation.

There are potentially two main causes for the DSO+T market model not capturing this price volatility: first, the model may not be calibrated and configured correctly; and second, the price behavior may be due to market behavior that is outside the capabilities of the modeling approach. Further effort to calibrate and tune the generator performance and production cost parameters combined with investigation of the effect of system parameters (such as reserve margins) could improve the representativeness of the market model. For example, requiring the system to dispatch more expensive peaker plants to address reserve shortfalls (due to outages or stricter fleet ramping constraints) could increase price variation. However, given the complex integrated nature of the SCUC and SCED optimization processes, successfully identifying key parameters and tuning them may be challenging. Alternatively, the price features seen in real markets may be due to behavior by market actors that is outside the capabilities of SCUC and SCED modeling approaches and assumptions. For example, out-of-market operation and self-scheduling by generators may alter prices in a way that diminishes market efficiency. In addition, the ability to exercise scarcity pricing (Meyn et al. 2018, page 89) could explain market volatility in the ERCOT market (but may not explain the results in PJM and CAISO).

Better understanding the practical and theoretical limits on capturing real market behavior warrants further investigation given the important role that market prices (value signals) play in transactive energy systems. In addition, understanding the acceptability (and impact) of these modeling limits on valuing transactive approaches needs to be kept in mind.

2.1.5 DSO Economic Performance

The simulation results are used in a detailed economic model to calculate the operating costs of each DSO (Pratt et al. 2022). In particular, each DSO's peak load impacts its generation capacity market payment as well as its overall transmission and distribution system infrastructure costs. The wholesale energy prices (day-ahead and real-time LMPs) form the basis for the cost of wholesale energy purchases. These expenses are combined with additional expenses (such as labor and materials) to form the total costs for a DSO. The cost breakdown for a typical DSO is shown in Figure 18. The overall proportions of expenses for this

DSO were similar for the other simulated DSOs. Wholesale energy and market costs represent over half of all DSO costs and are dominated by wholesale energy costs (29%), peak capacity charges (19%), and transmission charges (12%). Other wholesale costs, such as reserves, ancillary services, and ISO fees, account for less than 3%. Capital expenses are dominated by the distribution plant (9%) and nonmarket operational costs are dominated by operations and maintenance of the distribution infrastructure (24%). All other expenses account for less than 6% of the overall cost of doing business.

To determine the overall representativeness of the cost assumptions and estimating procedures used in this study, the overall blended average cost of electricity sold was calculated. Across all the DSOs simulated in the 200-bus model for the MR BAU case, the effective average annual rate varied from 9.7–14.3 cents/kWh with an average of 11.0 cents/kWh. This is slightly higher (by 7%) than the average 2016 U.S. value of 10.3 cents/kWh, and within the cited range (7.5–17.2 cents/kWh) for the 48 contiguous United States (DOE-EIA 2020). This suggests that the overall expenses are representative of typical DSO expenses in the country.

PJM provides example breakdowns of wholesale costs (PJM 2019). The DSO+T wholesale energy costs for all DSOs in the study's 200-bus model are within 10% of PJM data for 2018 and the relative proportions are representative. For example, on average in this study DSOs spend 48% of wholesale expenses on energy purchases (versus 63% for PJM), 28% on capacity costs (versus 20%), 18% on transmission charges (versus 15%), and ~4% on other wholesale costs such as ancillary services and reserves (versus 2% for PJM).

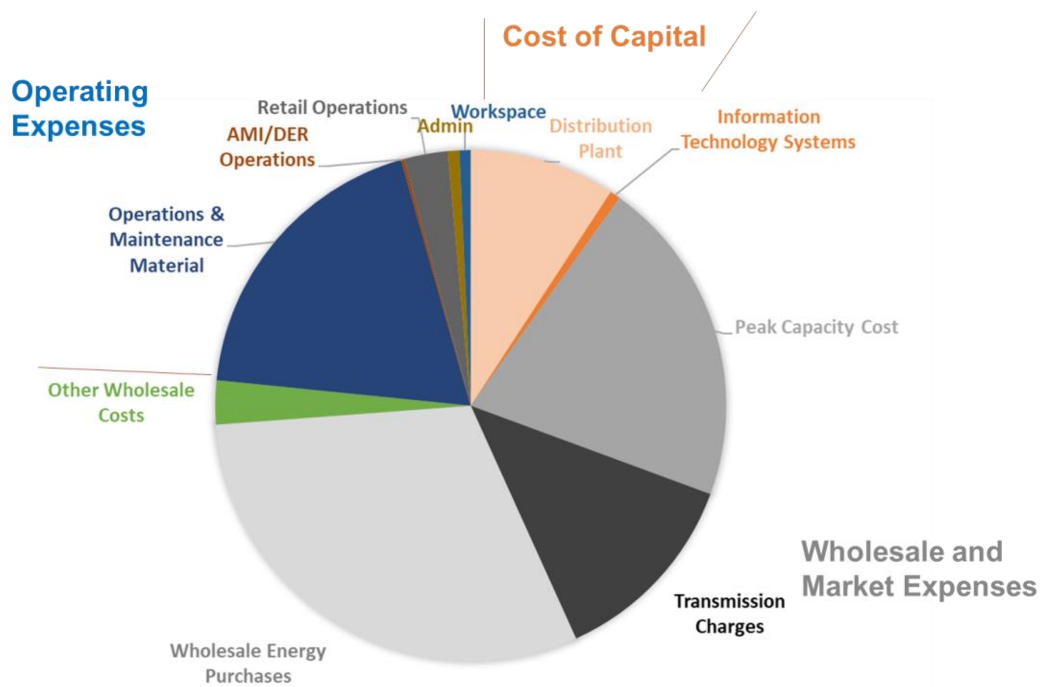


Figure 18. Typical DSO expense breakdown for the BAU case.

The result of the economic analysis framework is the ability to track value flows and financial payments through the entire electricity delivery system. As an example of this, Figure 19 provides a summary of the cashflow between grid entities to help illustrate primary stakeholders, key financial interactions, and level of granularity undertaken in the value analysis for this study. Figure 19 follows Sankey diagram conventions where quantities flow from left to right, where values flowing into the left side of an entity represent revenues, and values flowing out of the right side represent expenses. Starting at the far left of Figure 19, retail customers are charged for electricity service through a range of mechanisms (energy, demand, and connection charges). These charges represent the entire revenue for the DSOs who then use it to pay for their expenses to maintain and operate the distribution system, cover transmission charges and ISO fees, and generation expenses (wholesale energy purchases, capacity, and ancillary service payments).

Finally, this cash flow is used to pay for terminal expenses, which represent the downstream boundary of this study. Such expenses include the annualized cost of capital equipment and software infrastructure investments, real estate and workspace expenses, and labor and operation costs. In addition, generation costs are broken out by fuel class (e.g., coal, nuclear, natural gas, wind, and solar) and dedicated terminal expenses to capture the startup costs and the variable fuel and operations and maintenance costs associated with generation.

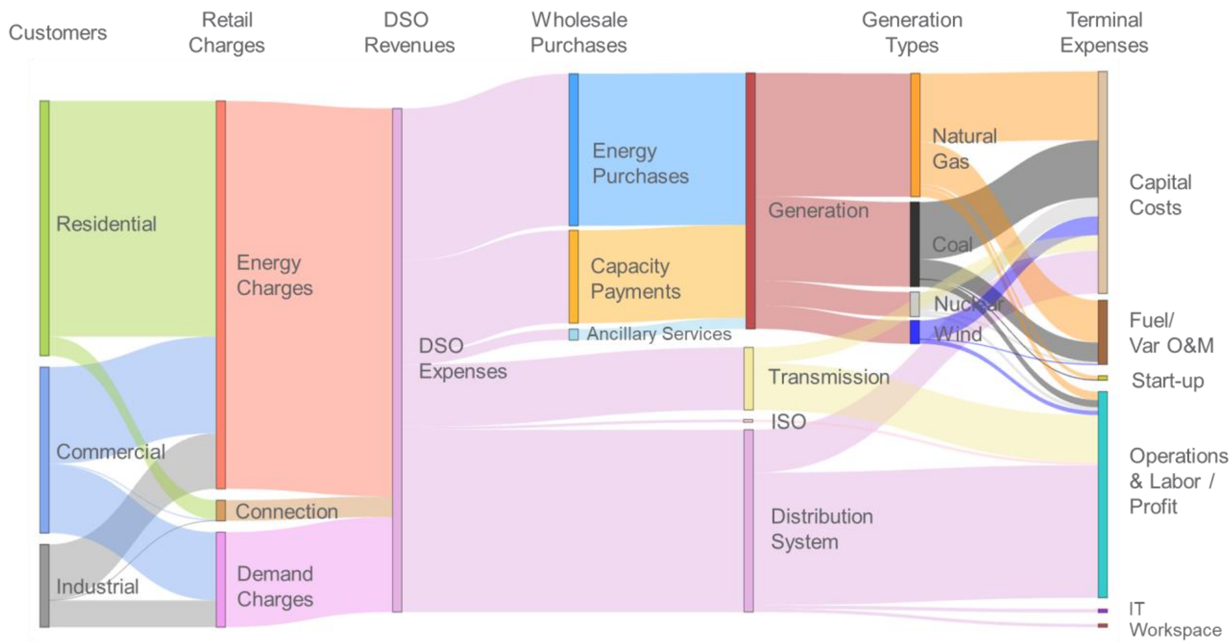


Figure 19. Summary of annualized cash flow between various stakeholders for the MR BAU case.

2.2 High Renewable Scenario

The resulting average generation and end-use loads for the HR BAU case are shown in Figure 20. The introduction of solar and growth of wind resulted in renewables accounting for ~40% of total generation over the course of the year. End-use loads were unchanged except for the introduction of EVs, which constituted 5% of total average load. While we assumed that an EV is present at ~30% of residential households, the assumed usage rates did not drive significant average load increases. The increased load from the EVs was more than offset by production from rooftop solar, resulting in a net reduction of total DSO average loads of 1.6 GW (4%). However, EVs did become a significant component (9%) of peak loads.

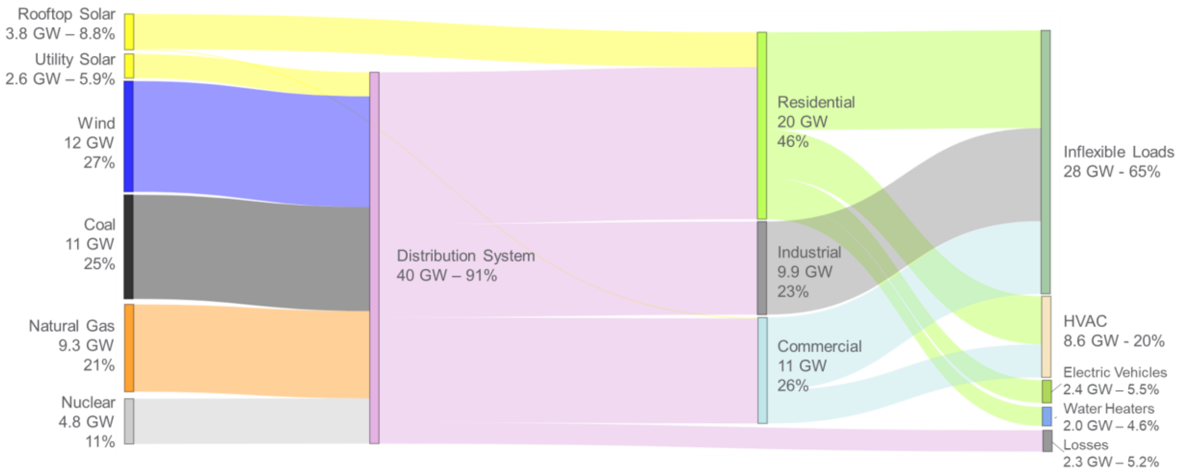


Figure 20. Annual average power by generation source, customer type, and end-use load for the HR BAU case (8-bus model).

The higher penetration of renewable energy substantially changes the daily and seasonal load profile, the need for dispatchable generation, and resulting wholesale prices as discussed below. This is due to the combined contribution of solar (rooftop and utility scale) and wind contributing >70% of generation over 10% of the hours of the year (compared to a >25% contribution in the MR BAU case.

Example load profiles are shown in Figure 21, which shows the load contributions (bottom to top) of industrial, plug, HVAC, water heater, and EVs. This load is reduced by the contribution of rooftop solar, resulting in the dashed brown line. The addition of distribution system losses results in the total distribution system load (shown in the solid black line). During the summer peak, generation from rooftop solar more than offsets the additional load from EVs, reducing peak load from the MR BAU case by 2.3 GW (5.6%; shown as the difference between the black and grey lines in Figure 21). Note that EVs contribute 9% of summer peak loads. This is because their load profile (dominated by afternoon and evening charging) coincides with the HR system peak which has now moved to the early evening. Furthermore, EV charging increases peak loads in the winter above the levels seen in the MR case (Figure 21, bottom) as EV charging occurs in the evening and night, after the sun has set, and coinciding with the nighttime peak heating load. This nighttime peak is exacerbated by significant daytime solar contributions resulting in large daily variations in distribution system net demand. The end result is that the largest variation in daily load no longer occurs during the summer peak but now occurs in January.

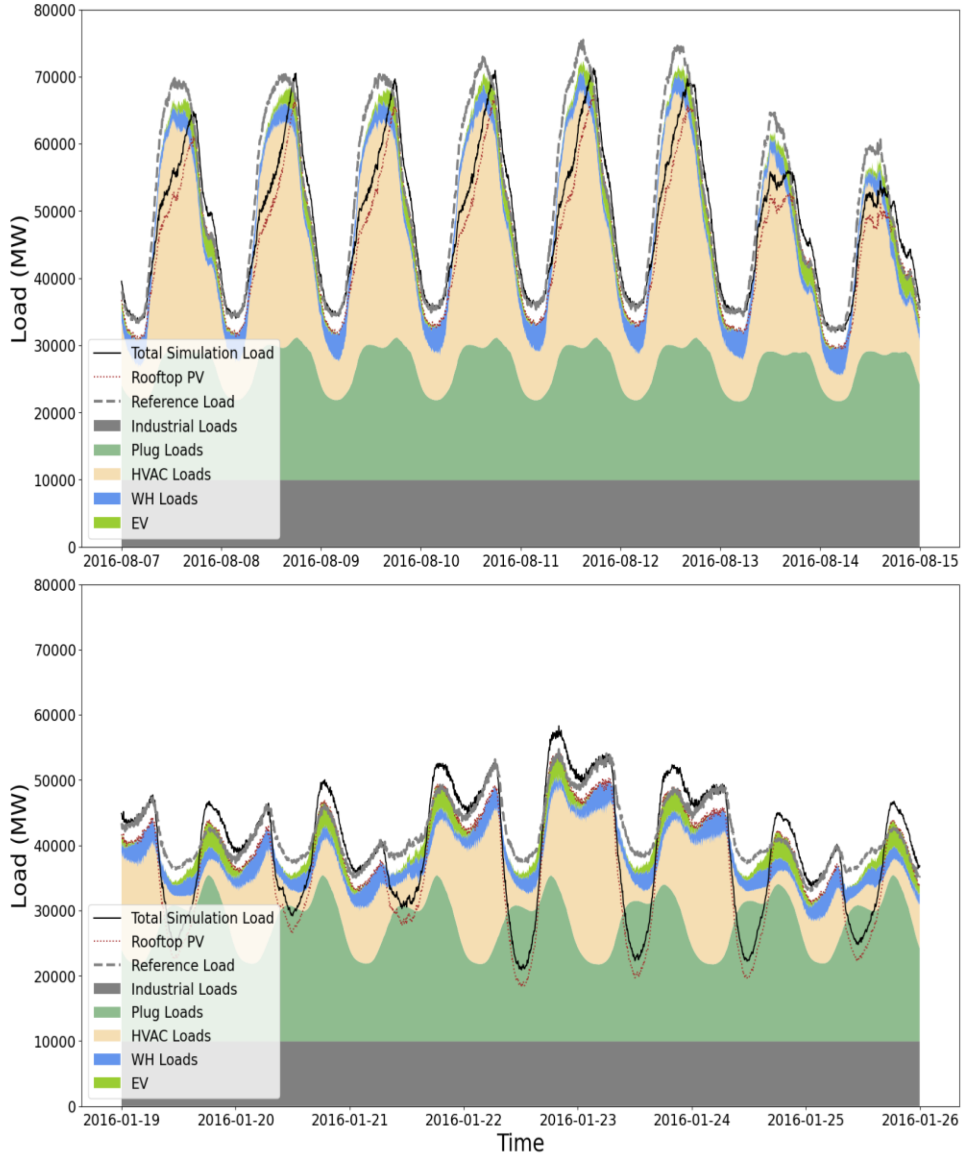


Figure 21. System load contributions by end use for peak demand (top) and maximum daily variation in load (bottom) for HR BAU. Total load for this scenario (solid black line) is shown in comparison to the total load for MR BAU (dotted grey line).

Figure 22 summarizes the system load for each month (top) and the daily variation in load (daily max load less the daily minimum load). This illustrates the trend seen in the HR scenario of solar and EV additions reducing the summer peak but increasing the winter peak and daily variation in winter and shoulder seasons. Overall, the average daily variation in load increased 2.5 GW (11%) between the MR and HR BAU cases. A summary of annual load statistics is provided for all cases in Section 3.1.

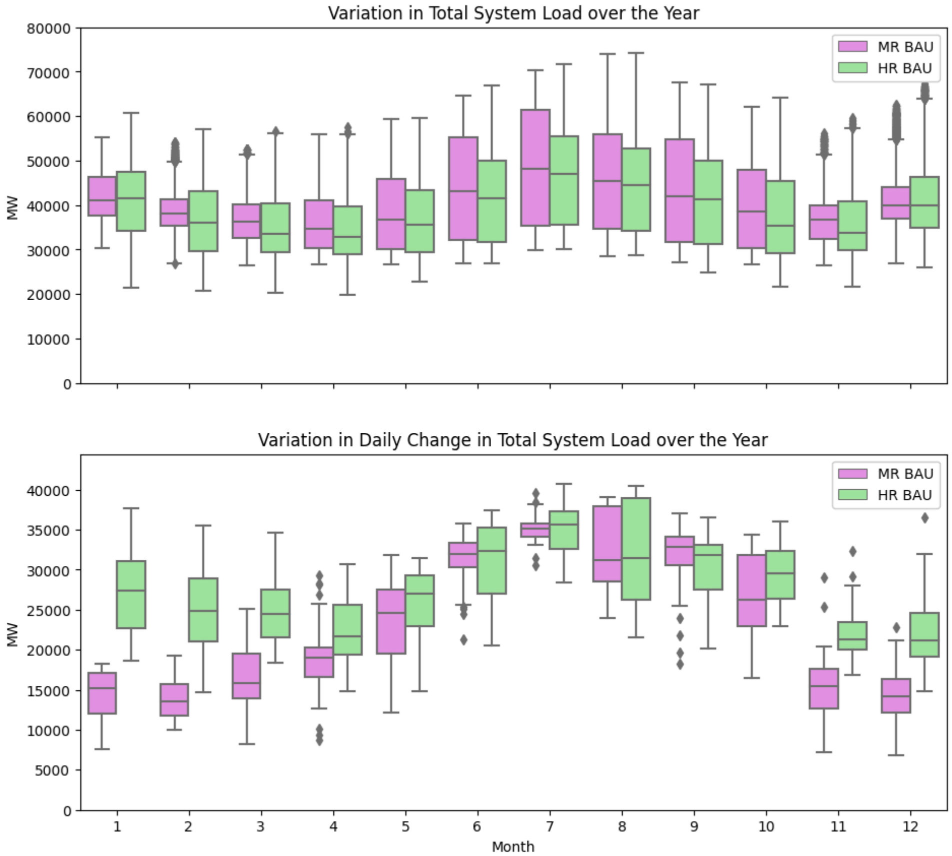


Figure 22. Monthly summary of system load (top) and daily variation in system load (bottom) for the MR and HR BAU cases.

The impact of changes in demand is compounded by additional wholesale wind and solar generation in the HR scenario. Figure 23 shows the corresponding bulk system generation dispatch. The increased contributions of wind and solar (both rooftop and utility scale) decrease the overall need for thermal generation but increase the ramping requirements. This is particularly pronounced in the winter (Figure 23, bottom). (Note that the significant impact of rooftop solar is accounted for in the reduced daytime total load.)

Due to the simulation challenges of converging the wholesale market model at very high levels of renewables (often with very low levels of dispatchable thermal generation relative to reserve requirements), curtailment of utility-scale renewable generation was enacted to ensure there was always >8 GW of dispatchable generation[1]. The resulting impact on wholesale day-ahead market prices is shown in Figure 24. The reduced need for dispatchable generation results in an 8% decreased average price, due to the reduced need for more expensive ‘peaker’ generators, but a 12% increase in the daily variation in price due to the increased ramping and starts. A summary of annual day-ahead LMP statistics is provided for all cases in Section 3.1.3, Table 9.

[1] 8 GW was identified as the lowest value that maintained sufficient convergence of the generation scheduling and dispatch solver.

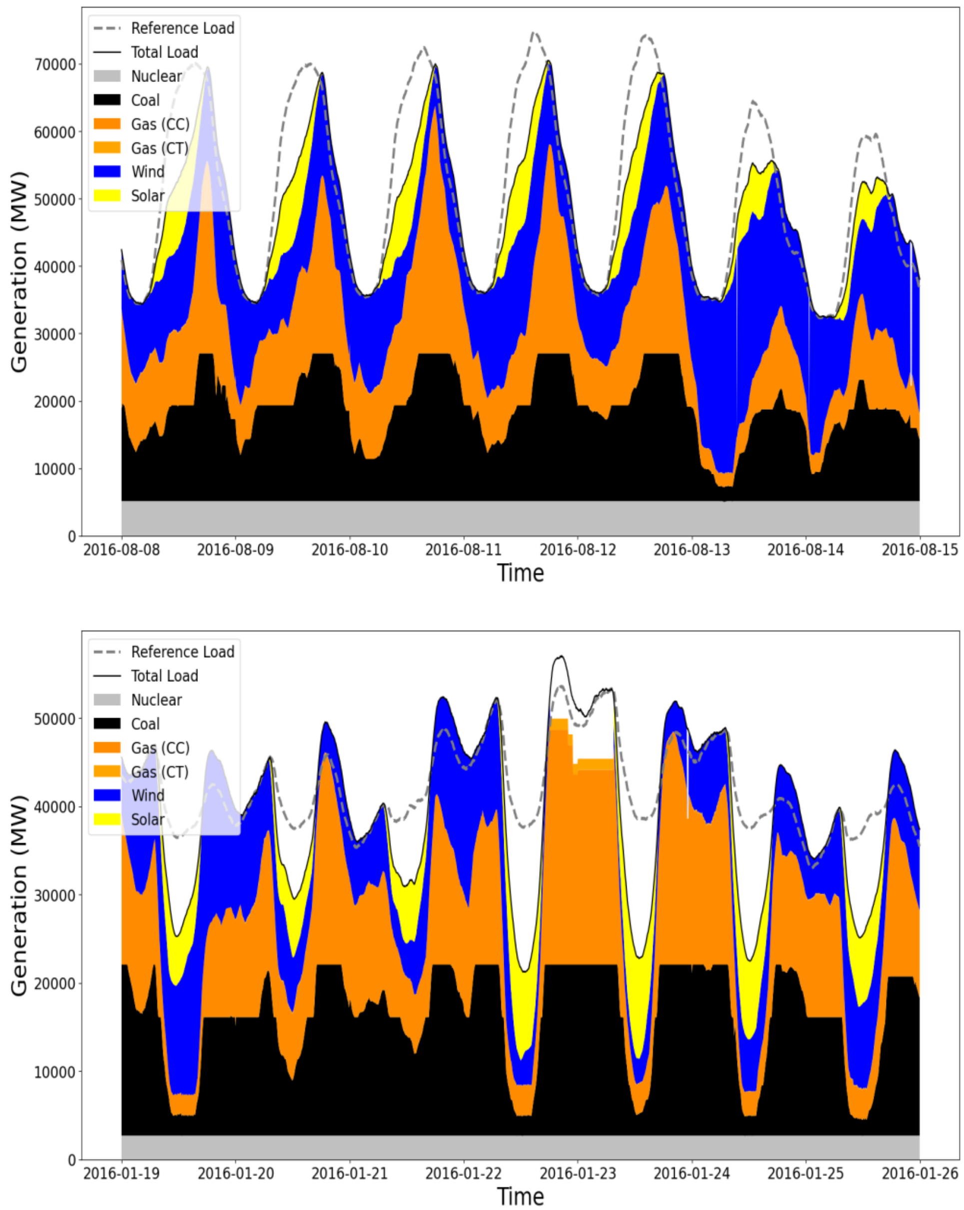


Figure 23. System generation contributions by type for peak demand (top) and the day of maximum daily variation in load (bottom) for HR BAU. Total generation for this scenario (solid black line) is shown in comparison to the total generation for MR BAU ("Reference Load" indicated by dotted grey line).

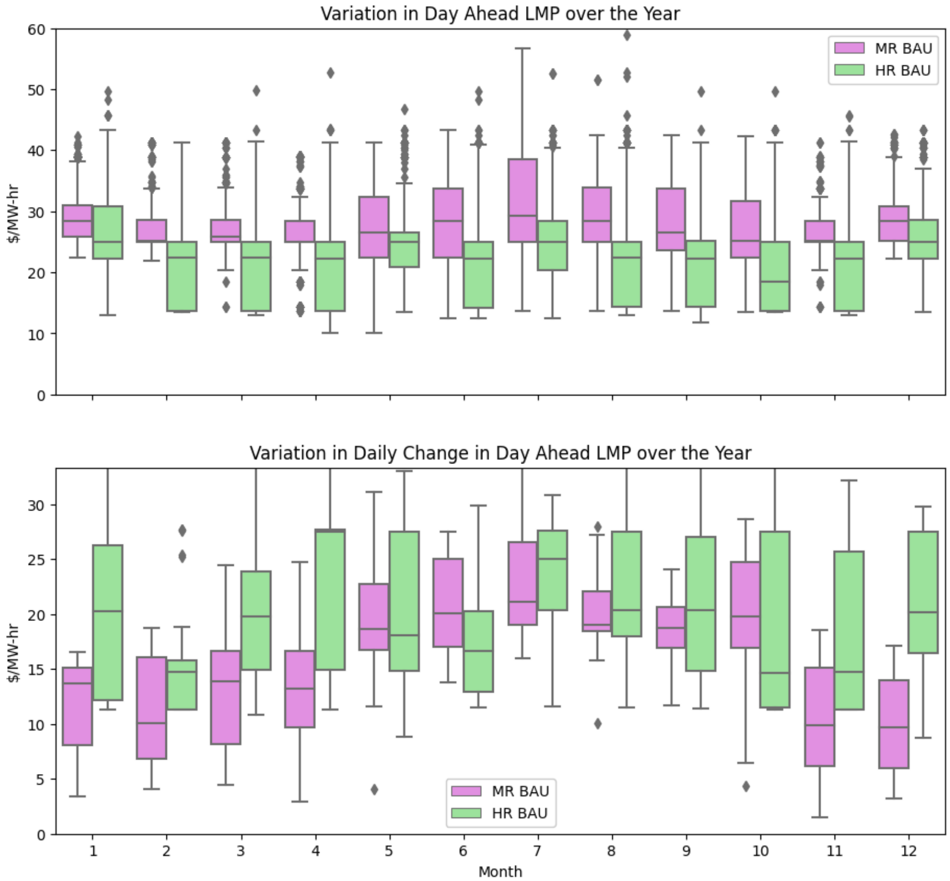


Figure 24. Monthly summary of day-ahead LMP (top) and daily variation in day-ahead LMP (bottom) for the MR and HR BAU cases.

2.3 Effect of Simulation Size (8-bus Versus 200-bus Results)

The DSO+T study results are based on a 200-bus model with transactive DSOs operating on 40 of those buses. These 40 DSOs represent ~90% of the system load (Reeve et al. 2022b; Section 5.6). A leaner 8-bus model was implemented to enable faster testing and exploration of the simulation with a single DSO on each bus. This section compares the results from the 8- and 200-bus models to determine the impact that simulation size has on critical system trends and metrics. The 8-bus model contained 11,929 buildings (11,190 residential and 739 commercial), 13,162 HVAC units, and 7,325 water heaters, representing a 1:952 scale of the ERCOT system. For the 200-bus model, the simulation contained 63,729 buildings (58,453 residential and 5,273 commercial), 73,704 HVAC units, and 36,624 water heaters, representing a 1:172 scale of the ERCOT system. This results in the 200-bus model having ~5.5 times the resolution on the distribution system (that is ~5.5 times more customers modeled) than the 8-bus model. Note that the relative resolution in terms of number of DSOs represented is nearly the same—exactly five times higher for the 200-bus model than the 8-bus model. By definition, the 200-bus model has a 25 times greater representation of the transmission system than the 8-bus model. The remainder of this section presents comparisons of system loads, generation dispatch, market prices, and overall economic metrics between the two models.

2.3.1 Annual System Load Results

Figure 25 shows that there are only small differences in daily load profiles between the 8- and 200-bus models. Annual summaries by month and as a function of load duration are shown in Figure 26 and Figure 27 and are summarized in Table 7. This confirms that both models predict average, peak, and minimum loads within 1% of each other. The 200-bus model does predict lower daily variations in load (by 7% on average). This may be due to several reasons. First, the 200-bus model uses actual scaled ERCOT load data to represent the load profiles of the 160 buses not simulated by DSO customer models. Overall, this only represents ~10% of the system load and while it does not appear to impact the average and peak loads, it may have dampened the daily variation in load. Second, the 200-bus model has 5 times as many weather locations on which the load profiles are simulated. This may better reflect the diversity of weather (and therefore load profiles) seen in the ERCOT region. Overall, these results show that the 8-bus model with its ~1:1000 customer representation provides adequate simulation resolution to capture load profiles.

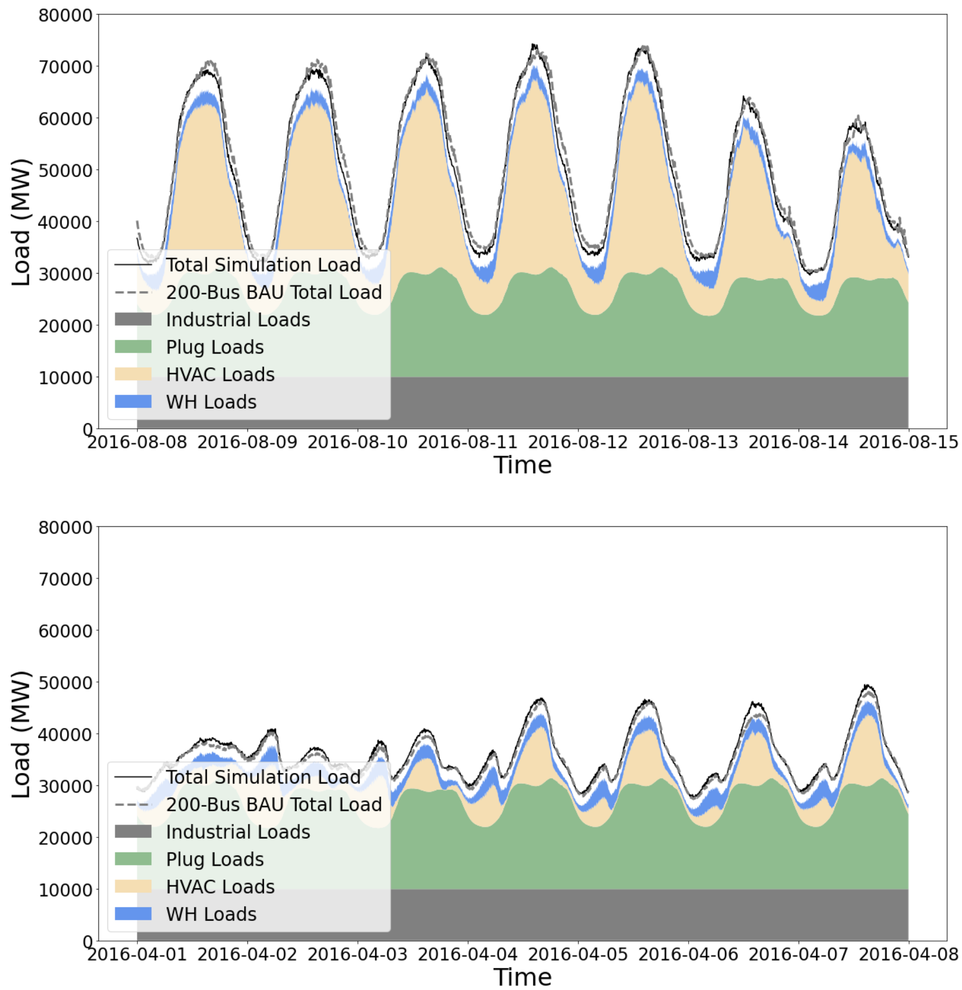


Figure 25. System load contributions by end use for week of peak (top) and minimum (bottom) load. 8-bus total system load (solid line) is shown in comparison total 200-bus system load (dotted line).

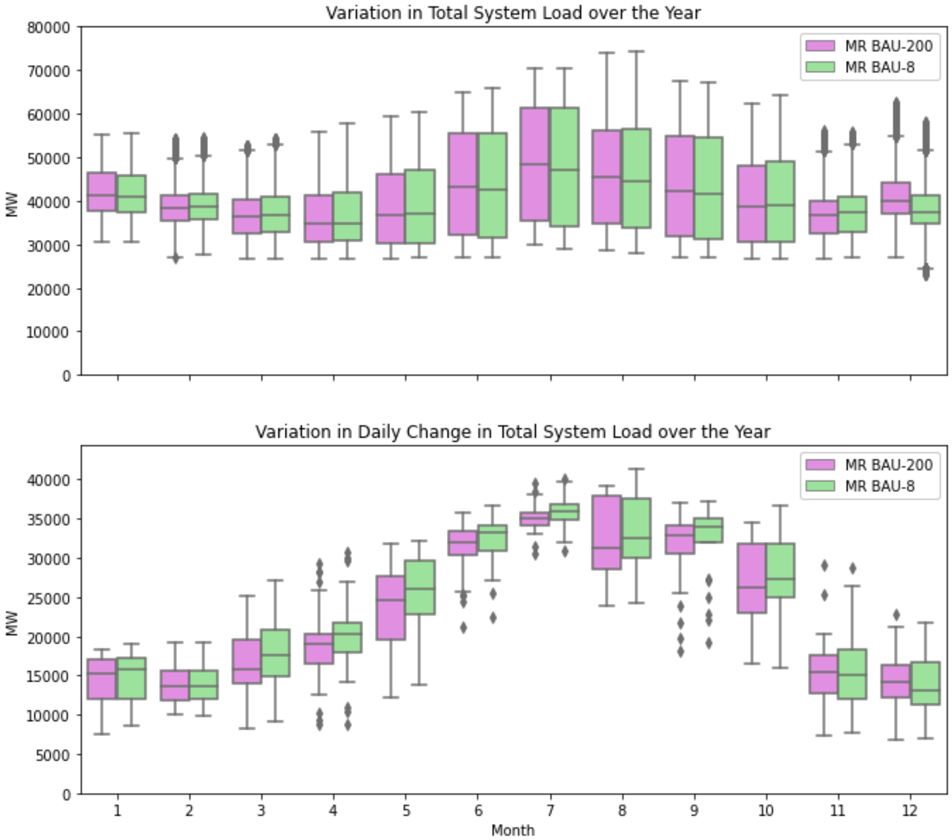


Figure 26. Monthly summary of system load (top) and daily variation in system load (bottom) for the MR BAU case comparing 8- and 200-bus results.

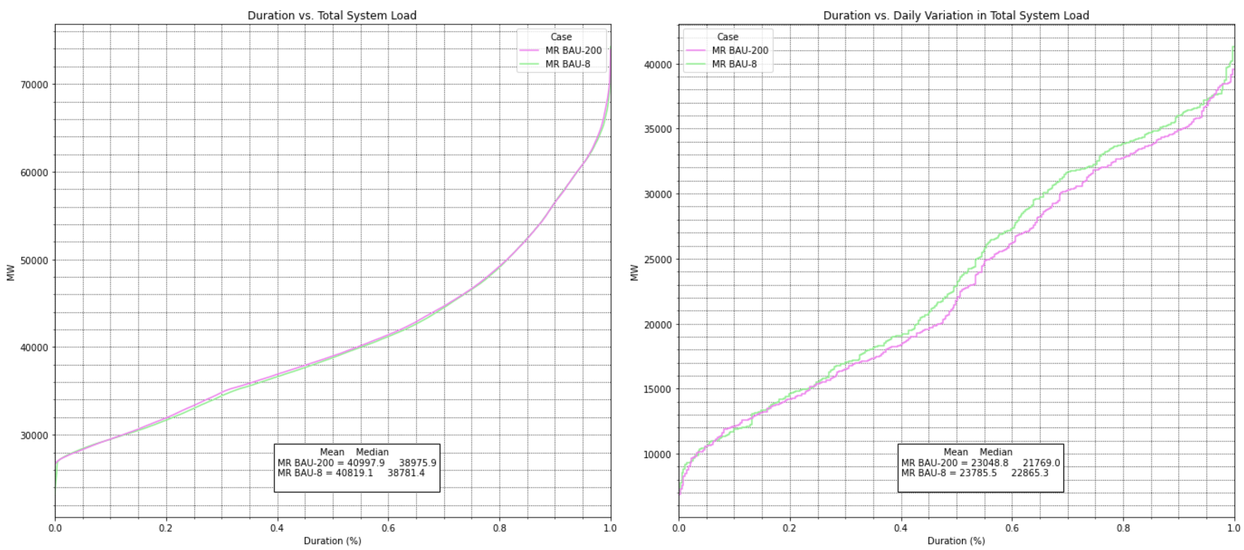


Figure 27. System load versus duration (left) and diurnal swing in system load versus duration (right) for the MR BAU case comparing 8- and 200-bus results.

Table 7. Comparison of the simulated grid load between the 8- and 200- bus models and actual 2016 ERCOT loads.

System Load (MW)	ERCOT	8-Bus		200-Bus		8-Bus vs 200-Bus
		DSO+T	% Diff	DSO+T	% Diff	% Diff
Average	39,191	41,075	4.8%	40,998	4.6%	0.2%
Max	70,359	74,265	5.5%	73,938	5.1%	0.4%
Min	24,098	26,636	10.5%	26,545	10.2%	0.3%
Average Daily Range	16,795	24,653	46.7%	23,049	37.2%	7.0%
Max Daily Range	29,146	41,308	41.7%	39,588	35.8%	4.3%
Min Daily Range	5,036	7,788	54.6%	6,861	36.2%	13.5%

2.3.2 Generation Dispatch

A comparison of the bulk system generation fleet dispatch is shown in Figure 28 and summarized in Table 8. The generation dispatch in both cases is practically identical, with annual generation contributions by fuel type within 2% between models. This is expected as the generation fleet is identical in both models. Furthermore, the system-level load profiles are practically identical as was discussed in the proceeding section. The only remaining difference is the transmission system model (to be discussed in the next section). The transmission system will influence generation scheduling and dispatch when transmission network constraints (i.e., congestion) prevent cheaper generators from operating. This is expected to occur infrequently during the year when peak loads or network outages cause system congestion. There may be some differences in generator scheduling and dispatch due to challenges in solving the SCUC and SCUD problems relative to the convergence criteria for the 200-bus versus the 8-bus networks.

Table 8. Summary of system capacity and production by generator type for the MR scenario versus ERCOT and the nation.

	Generation				8-Bus vs 200-Bus
Fuel	ERCOT	U.S.	MR-200 bus	MR-8 bus	% Difference
Nuclear	12%	20%	12.54%	12.52%	-0.16%
Coal	29%	30%	38.17%	37.62%	-1.44%
Natural gas	44%	34%	34.84%	35.42%	1.66%
Wind	15%	6%	14.45%	14.44%	-0.07%
Solar (utility scale)	0.2%	1.0%	-	-	-
Solar (distributed)	-	-	-	-	-
Other	-	9%	-	-	-

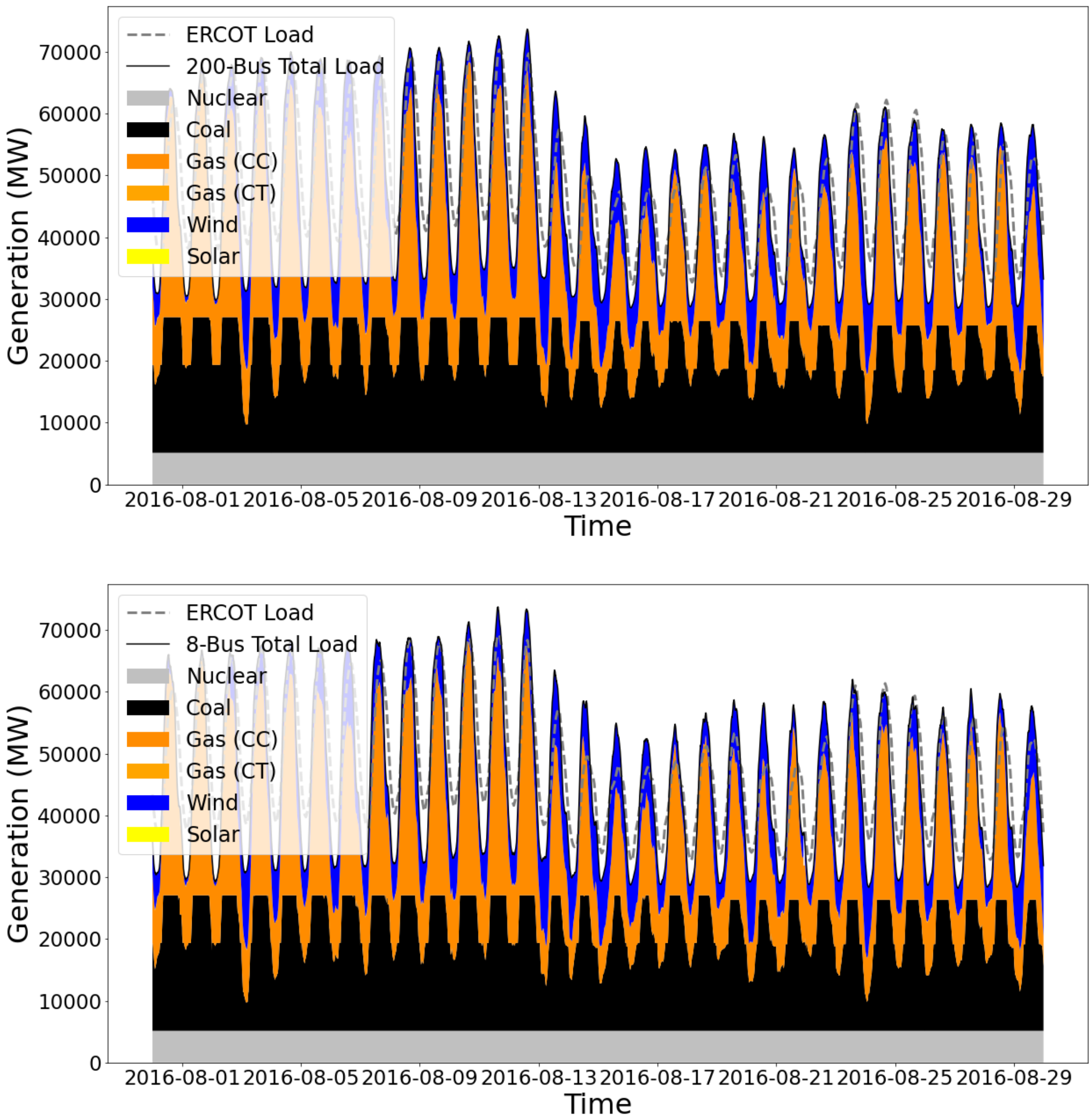


Figure 28. Comparison of real-time generation dispatch for the MR BAU case 200-bus model (top) versus the 8-bus model (bottom) for August 2016.

2.3.3 Transmission System

The transmission system has the largest disparity in resolution between the 8- and 200-bus models. The transmission system networks for each model are shown in Figure 29. As will be discussed in the next section, the 8-bus model exhibits lower variation in day-ahead prices. This includes geographic variation. Figure 30 shows the normalized transmission line capacity utilization and real-time LMP during the system peak load (2pm on August 12, 2016). The 200-bus model has nodal real-time LMPs that range from $13.73/MW-hr to the price cap of $2000/MW-hr with a system average of $83.49/MW-hr. In comparison the LMP price contours are not plotted in Figure 30 for the 8-bus model as all nodes have an identical price of $45.69. This suggests that the 8-bus model provides insufficient resolution to reflect spatial price variation.

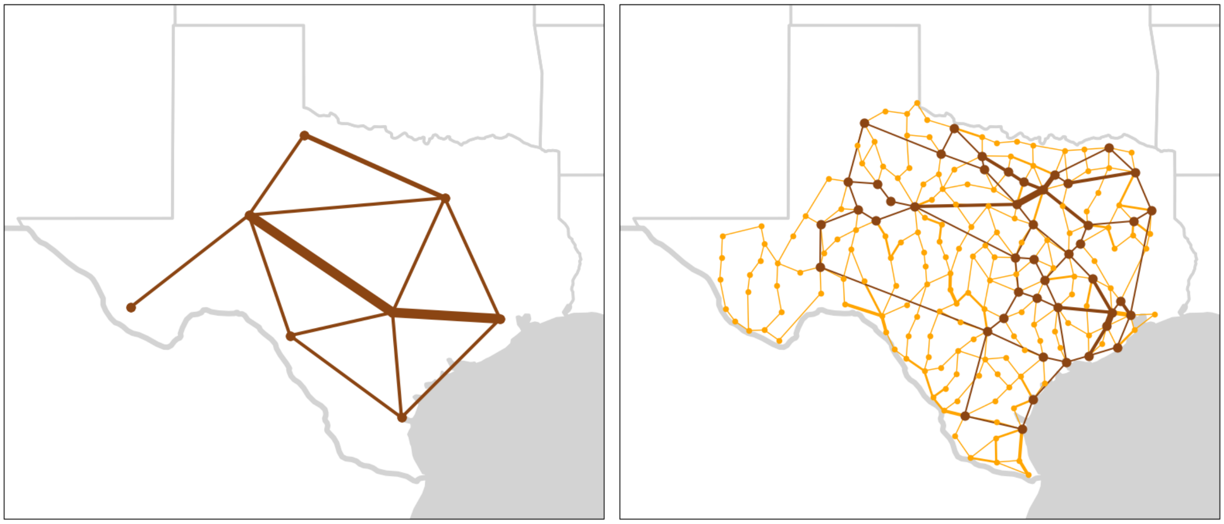


Figure 29. Example of 8-bus (left) and 200-bus (right) transmission networks. 345 kV lines are shown in brown and 138 kV lines in orange. The line thickness is proportional to its MVA rating.

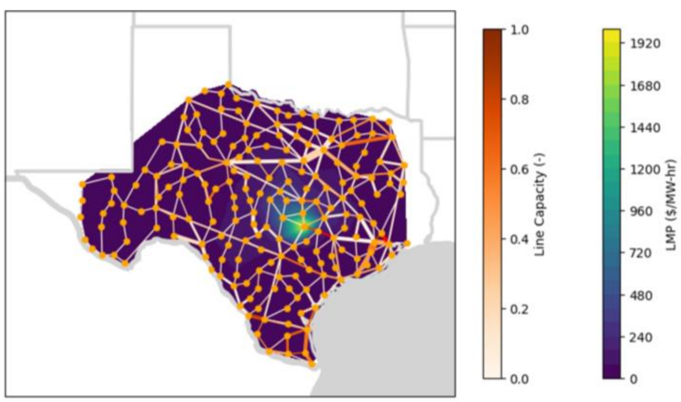


Figure 30. Example of 200-bus real-time LMP and line capacity of their transmission networks during the system peak (2pm August 12, 2016).

2.3.4 Annual Wholesale Price Results

The 200- and 8-bus simulations calculate identical (within ~1%) annual average (for all nodes) day-ahead and real-time LMPs (see Table 9). However, there are differences between the two cases regarding the daily variation of LMPs. This can be seen in Figure 31 and Figure 33 for day-ahead LMPs and Figure 32 and Figure 34 for real-time prices. The 8-bus case has slightly larger daily variation in real-time LMPs but is within 10% of the 200-bus simulation. When averaged across all DSOs the 8-bus simulation does substantially underestimate the daily variation in day-ahead LMPs in comparison to the 200-bus case. This is likely due to a small number of nodes in the 200-node case experiencing a few very high prices (and hence price variations) in the months of March, April, July, and November as is shown in Figure 31. A comparison of duration curves for daily variation in LMP for a typical DSO (DSO #1) shows that the both the 8- and 200-bus cases under-represent daily LMP variations compared to real-world ISO data. The difference in predicting the variability of wholesale prices (and underprediction versus real markets as seen in Section 2.1.4) is important as the majority of the transactive agents' strategy is based on forecasts of the day-ahead price variation. Underrepresenting the daily variation in price leads to an underestimation of the value and incentive of transactive agents providing demand flexibility. This is an area that warrants improved understanding and capability.

Table 9. Summary of annual average and average daily change in day-ahead and real-time LMPs ($/MWh) for each case. (Averaged for all DSOs.)

	MR-200 bus	MR-8 bus	% Difference
Day-Ahead LMP: Annual Average	29.19	28.91	-1.0
Day-Ahead LMP: Average Daily Range	29.21	17.01	-41.8
Real-Time LMP: Annual Average	27.01	27.01	0.0
Real-Time LMP: Average Daily Range	22.25	24.69	9.8

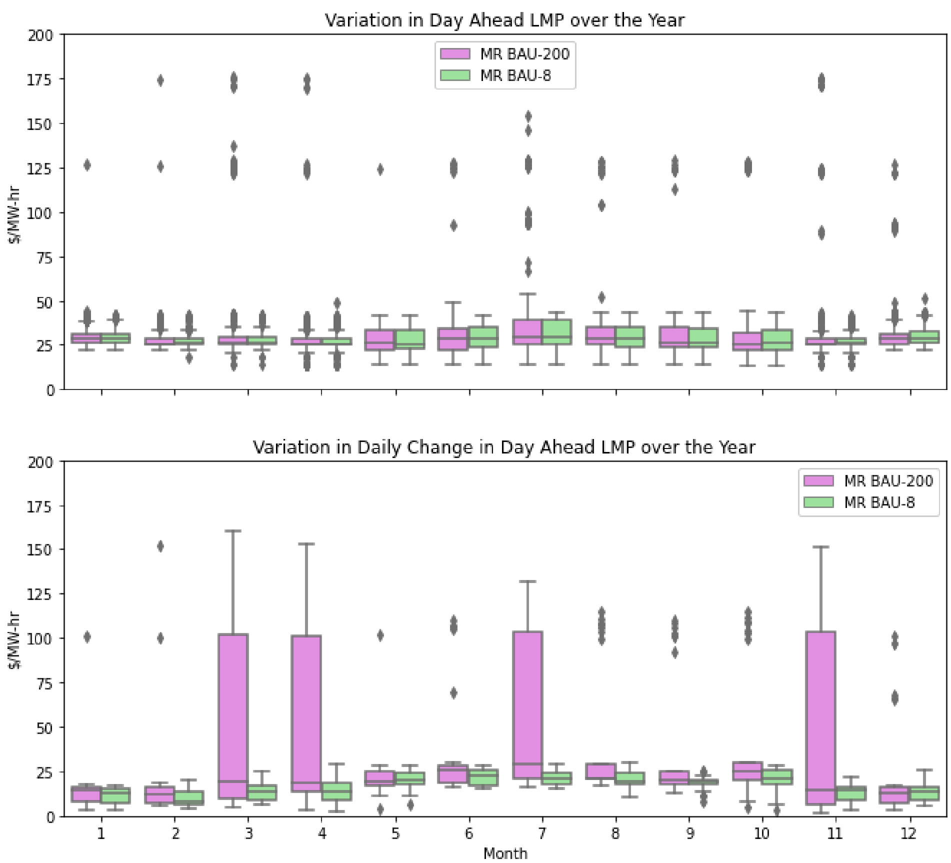


Figure 31. Monthly summary of average DSO day-ahead LMP (top) and daily variation in day-ahead LMP (bottom) for the MR BAU case.

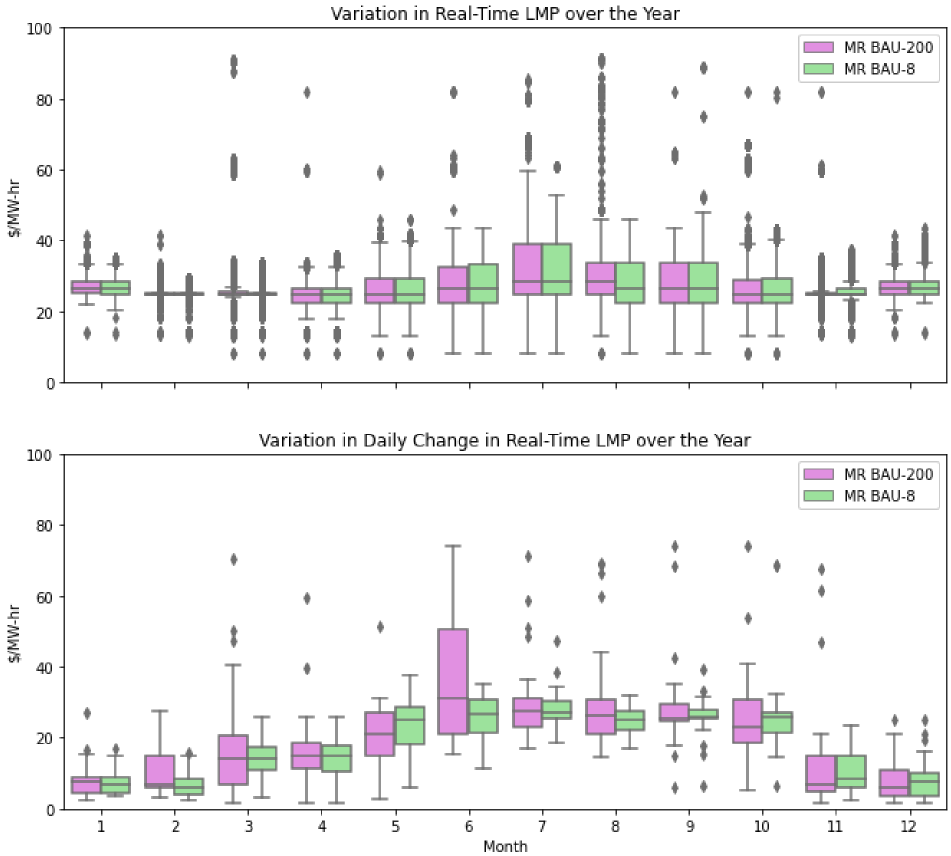


Figure 32. Monthly summary of average DSO real-time LMP (top) and daily variation in real-time LMP (bottom) for the MR BAU case.

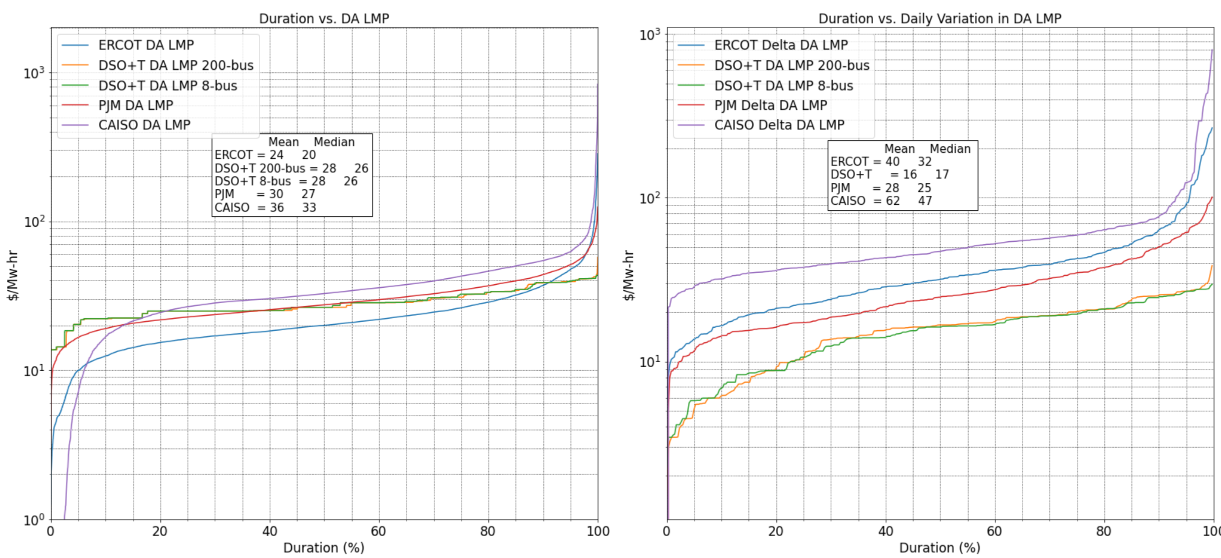


Figure 33. Day-ahead LMP versus duration (left) and daily variation versus duration (right) for the MR BAU case comparing 200- and 8-bus results (DSO #1) against ISO results.

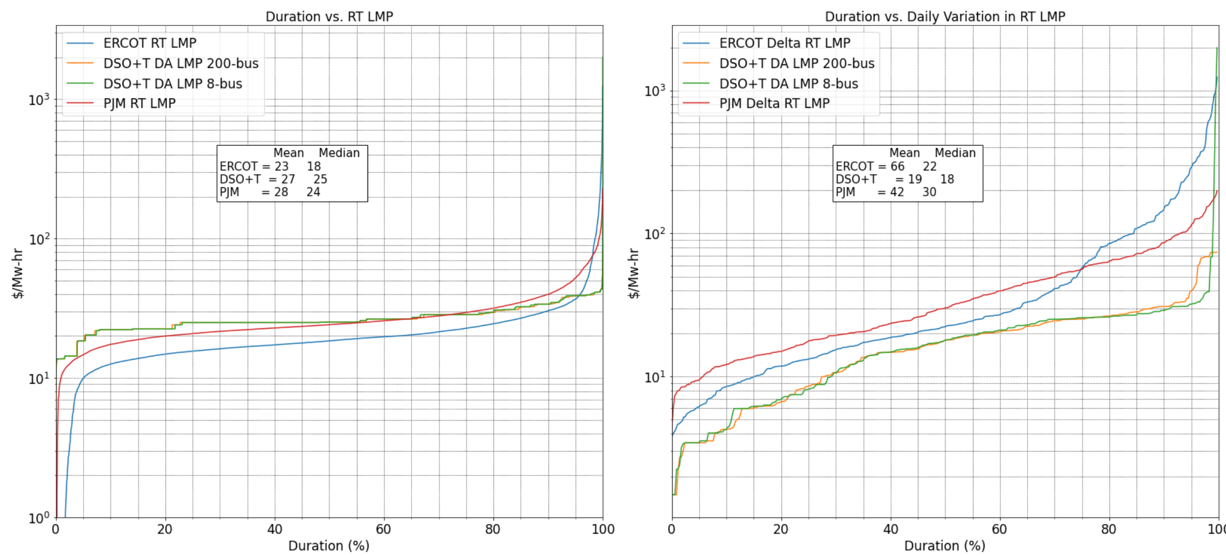


Figure 34. Real-time LMP versus duration (left) and daily variation versus duration (right) for the MR BAU case comparing 200- and 8-bus results (DSO #1) against ISO results.

2.3.5 DSO Annual Economic Performance

The peak loads, energy load profiles, and resulting wholesale market prices all impact the DSOs' cost basis. Unfortunately, making a direct cost comparison for an individual DSO is not possible due to the lack of common DSOs between the two cases. Furthermore, the 200-bus simulation models 40 DSOs representing ~90% of the system load while the 8-bus simulation models all 100% of system load. Despite these challenges a comparison of aggregate system-wide DSO costs, broken out by element, is provided in Table 10 for the MR BAU case. The 200-bus simulation has a total operating cost for all 40 DSOs of $30.7B compared to $33.6B for the base case. This 8.9% lower cost is not quite commensurate with the fact that the 40 DSOs in the 200-bus simulation are representing 10.2% fewer customers. In addition, the effective cost of electricity sold for the 200-bus MR BAU case was 11.00 cents/kW-hr compared to 10.56 cents/kW-hr for the 8-bus case, a 4% increase.

A comparison of the cost elements in Table 10 explains this small increase in relative overall cost. Cost elements that scale linearly with DSO size (such as wholesale purchases, capital costs, and materials) have a proportional contribution that is within 1-4% between the two cases. However, labor and operations costs (such as O&M labor, AMI/DER operations, retail operations, and admin) are proportionally 9-30% higher in the 200-bus case. This is because the 200-bus case has DSOs that are, on average, 5.5 times smaller than the 8-bus case. This results in higher relative costs for elements that do not scale linearly for smaller DSOs. While this is a second-order effect in the total cost basis, it is an important reminder that some DSOs (e.g., rural cooperatives) may experience higher implementation costs on a per customer basis.

Table 10. Comparison between the 8- and 200- bus models of the cost ($k) structure for all DSOs. (The right column shows the difference in relative contributions not absolute cost.)

Cost Element	200-bus MR BAU		8-bus MR BAU		Difference in Proportion (%)
Distribution Plant	2,543,076	8.6%	2,863,913	8.9%	-3.3%
IT Systems	210,157	0.7%	236,616	0.6%	9.5%
Peak Capacity Cost	5,577,109	19.2%	6,204,978	19.9%	-3.6%
Transmission Charges	3,667,702	12.2%	4,182,136	12.1%	0.5%
Wholesale Energy Purchases	9,592,395	29.3%	10,157,741	29.4%	-0.5%
Other Wholesale Costs	808,731	2.7%	922,164	2.7%	0.5%
O&M Material	5,571,634	18.2%	6,371,527	18.3%	-0.4%
O&M Labor	1,110,709	4.1%	1,230,851	3.7%	8.8%
AMI/DER Operations	82,044	0.2%	65,623	0.2%	17.9%
Retail Operations	809,046	2.9%	886,858	2.7%	9.0%
Admin	435,190	1.0%	260,777	0.7%	30.5%
Workspace	198,681	0.8%	214,172	0.7%	10.0%
Total	30,656,910	100%	33,642,802	100%	-

3.0 Transactive System Results

This section provides the overall system-level results of the DSO+T Study. It starts with a summary of the impact of transactive coordination of the distributed flexible customer assets on the system-wide load profiles, generation dispatch, and resulting wholesale market prices. The resulting changes to aggregate DSO and customer annualized cash flows show the overall financial benefit of a DSO+T implementation. A sensitivity analysis is included to evaluate the robustness of these savings.

3.1 System-Level Impacts

The study indicates significant changes to the system load profile, generation, and energy markets when comparing the transactive and BAU cases. These are detailed in the following sections

3.1.1 System Load Impacts

This section provides a summary of the load profile changes resulting from the various transactive cases. The combined impact of the various DERs on total system load can be complex. To aid the following discussion, Figure 35 provides a summary of typical DER behavior and their representation on load plots for the HR battery case for a peak load day in August.

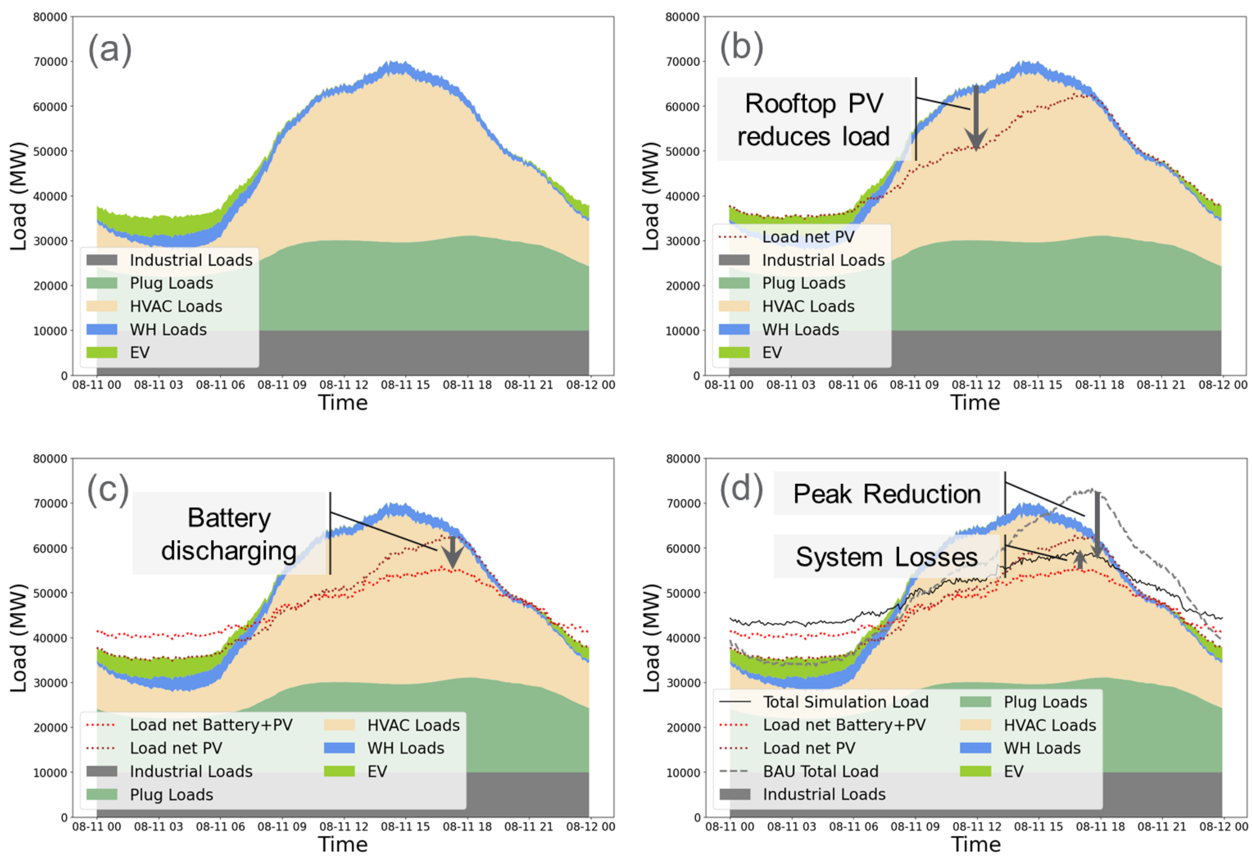


Figure 35. Load profiles plots showing stacked end-use loads (a), the reduction in peak loads due to rooftop solar (b) and battery discharging (c), and the resulting system load (d) after distribution losses are included. (Results shown for the HR battery case.)

All flexible and inflexible customer assets that are incapable of feeding power back onto the grid are shown as stacked loads in Figure 35a. This includes industrial, plug (or miscellaneous), HVAC, water heater, and EV loads (which are flexible in this case and have shifted to nighttime). These loads are then offset, in part, by rooftop solar generation (Figure 35b). The load profile is further flattened by the charging and discharging of the battery fleet (shown as the difference between the brown and red dashed lines in Figure 35c). The dashed red line in Figure 35d represents the sum of all metered customer loads. The inclusion of distribution system losses results in the total distribution system load (the black line in Figure 35d). Comparing this to the HR BAU system load (the gray dashed line) illustrates the reduction in peak load between the two cases. The reduction in peak load is complemented by an increase in minimum load due to the shift in EV charging and the addition of battery charging.

The transactive coordination of flexible assets disincentivizes consumption during periods of high prices (typically associated with high electrical demand during the afternoon and evening) and incentivizes relatively higher electrical consumption (for example, battery and EV charging, HVAC precooling, water preheating) during periods of low prices (typically during nighttime or periods with abundant renewable generation). These trends can be seen in the load profiles of Figure 36 showing the impact of the battery and flexible load operation on the daily system peak load experienced in August in the MR case. For the battery case, the net result of charging and discharging (the dashed red line) decreases system peak loads by ~10% while increasing the minimum system loads and decreases the daily variation in load by ~30% for the peak day. Similar trends are seen for the flexible loads case where water heater and HVAC loads are shifted out of peak periods.

Similar load profiles for winter days are shown for the two transactive MR cases in Figure 37. Much smaller reductions in peak load and daily load variation are seen in this case. This is due to the much smaller overall load variation resulting in more modest changes in wholesale electricity prices (see Section 3.1.3). This in turn provides less incentive to assets to provide flexibility.

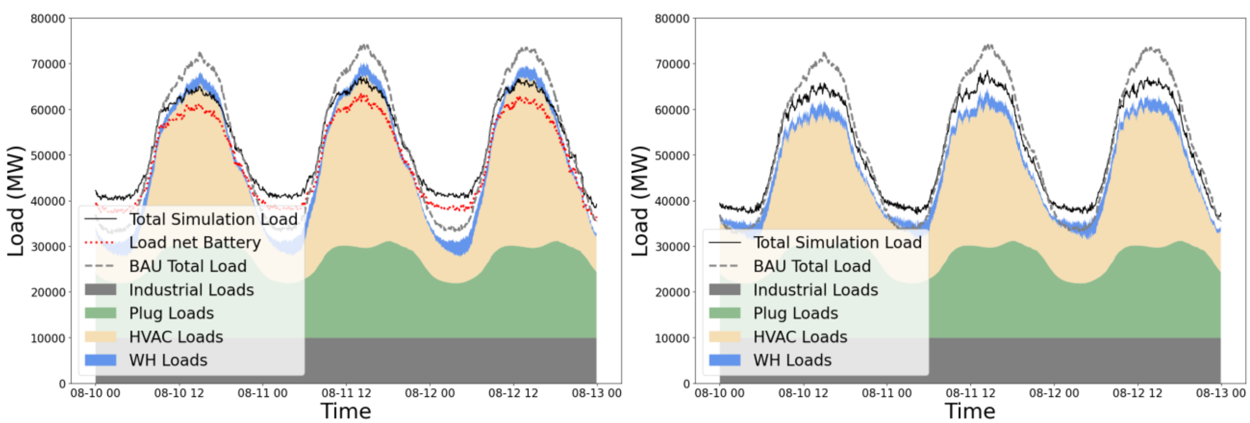


Figure 36. Peak summer load profiles for the battery case (left) and the flexible load case (right) for the MR scenario.

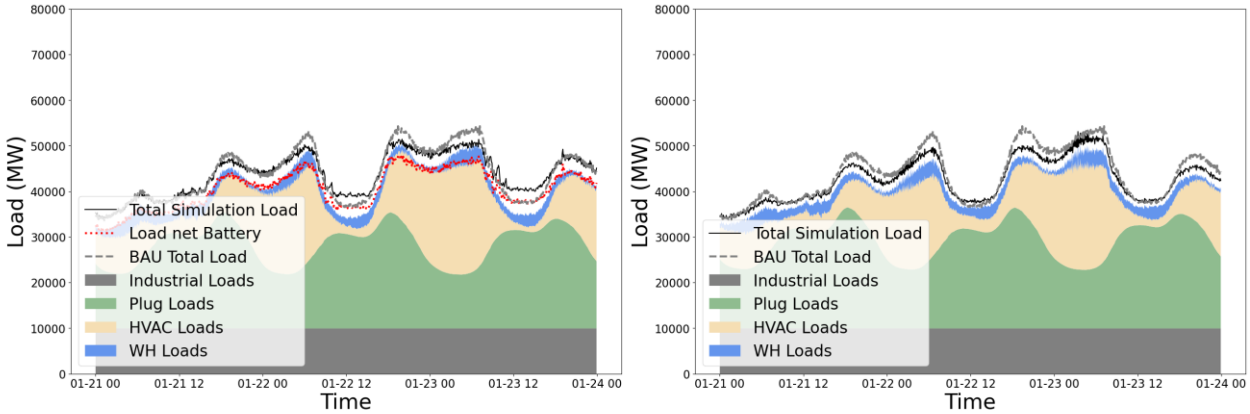


Figure 37. Winter load profiles for the battery case (left) and the flexible load case (right) for the MR scenario.

A summary of the annual variation in system loads and diurnal load change for the MR and HR scenarios are shown in Figure 38 and Figure 39, respectively, and summarized in Table 11.

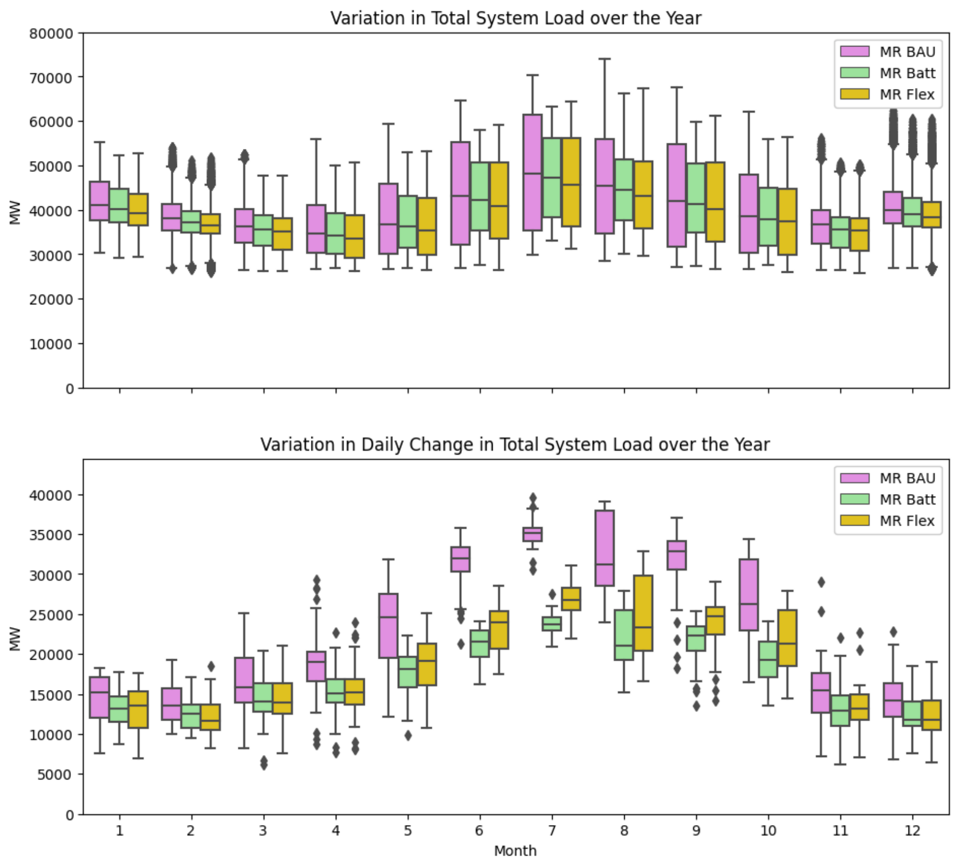


Figure 38. Monthly summary of system load (top) and diurnal variation in system load (bottom) for the MR scenario.

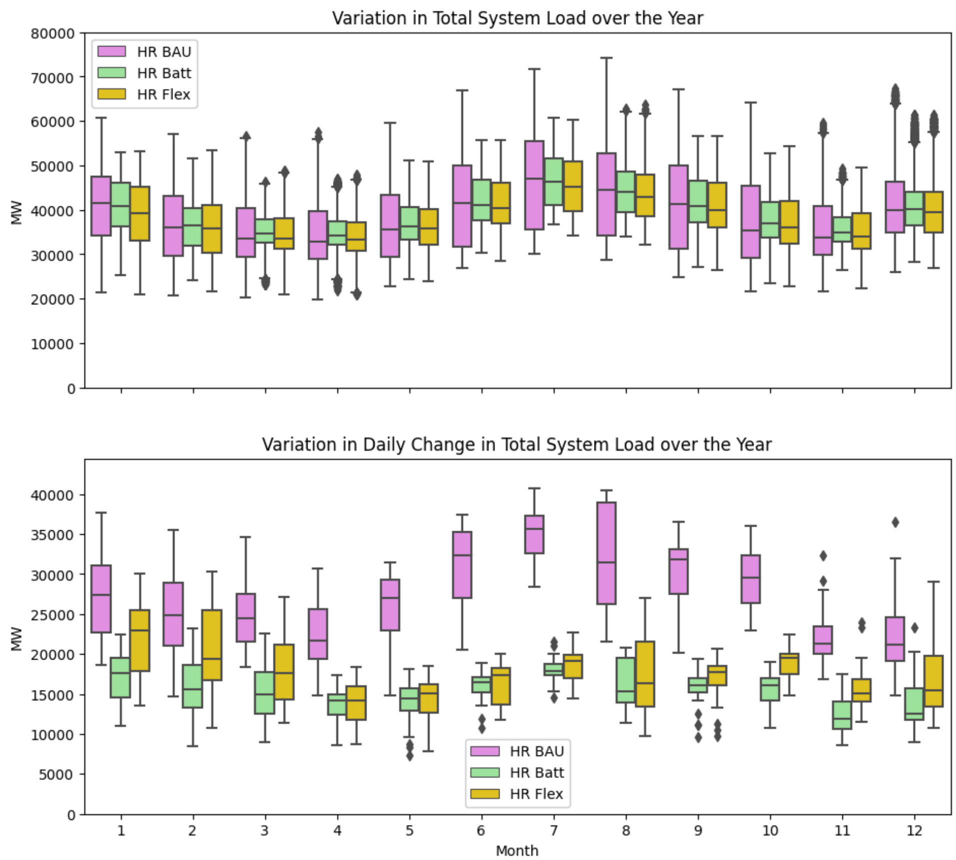


Figure 39. Monthly summary of system load (top) and daily variation in system load (bottom) for the HR scenario.

Table 11. Summary of annual average and maximum loads as well as average daily change in load for all cases.

	MR BAU	MR Battery	MR Flex	HR BAU	HR Battery	HR Flex
Average (MW)	41,000	39,900 (-2.8%)	39,100 (-4.7%)	39,400	39,400 (0.1%)	38,600 (-2.0%)
Max (MW)	73,900	66,300(-10.3%)	67,400 (-8.8%)	74,300	62,800(-15.5%)	63,800 (-14.2%)
Min (MW)	26,500	26,300 (-1.1%)	25,800 (-2.8%)	19,800	21,900 (10.8%)	20,900 (5.8%)
Average Daily Range (MW)	23,000	17,100(-25.6%)	18,300(-20.4%)	27,300	15,400(-43.8%)	17,400 (-36.3%)

3.1.1.1 Battery Cases

The battery cases substantially reduce the system peak loads and diurnal load swing (as shown in Figure 38 and Figure 39). In the MR scenario, the system maximum load is reduced approximately 10%. In the HR scenario, the peak load reduction is substantially higher (>15%). This is due to the inclusion of smart EV charging (V1G) in the HR scenario that also contributes to load reduction as shown in Figure 40. The HR BAU case experienced a peak EV charging rate of ~6 GW in the afternoon of the peak day (August 11). This is reduced to practically zero in the battery and flexible load cases, reducing peak load by 9%. The system loads are then further flattened by battery charging and discharging.

Figure 39 and Figure 41 show that for the high renewable scenario, batteries and EV provide significant load reduction in the winter, unlike in the MR scenario. This is due to increased BAU daily load variation caused by rooftop solar and EVs. Rooftop solar causes a significant reduction in net load during the middle of the day when low heating requirements already result in the minimum daily system load. In addition, the EV load coincides with the daily peak evening system load. The combined results are daily variations in load and wholesale electricity prices that are similar in magnitude to the peak summer variations seen in the MR scenario. These price variations provide sufficient incentives for batteries and EVs to provide flexibility and reduce load variation.

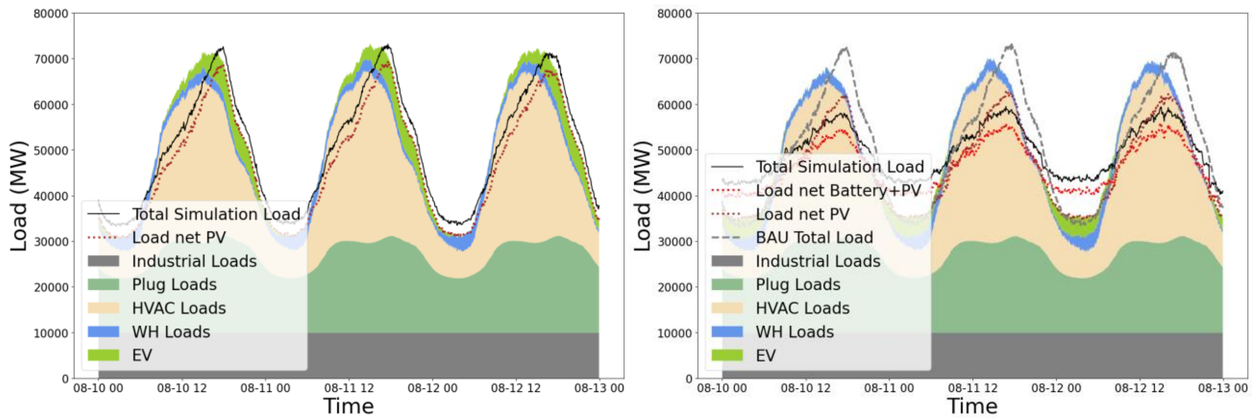


Figure 40. Comparison of BAU (left) and battery case (right) load profiles for the HR scenario showing the significant summer peak load reduction due to shifting EV charging and battery charging and discharging.

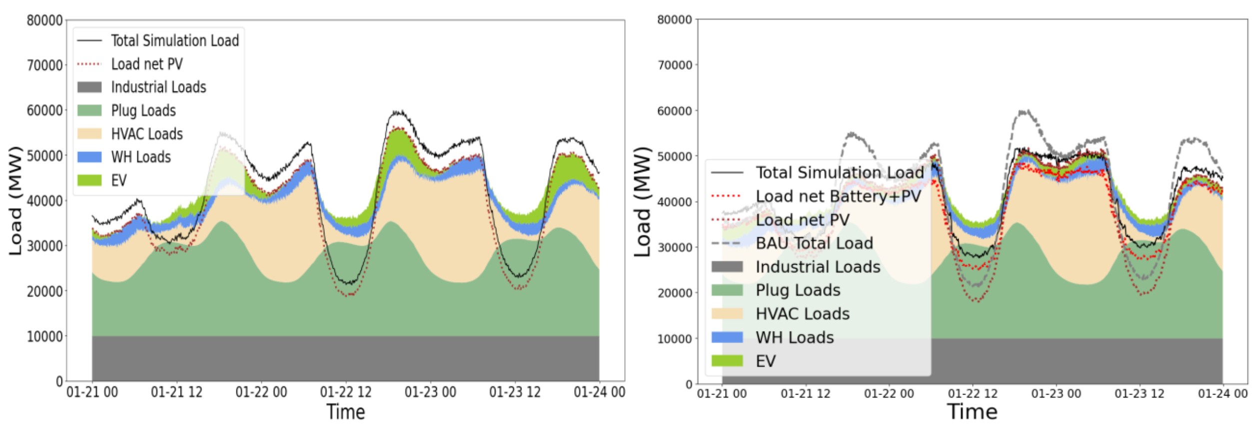


Figure 41. Comparison of BAU (left) and battery case (right) load profiles for the HR scenario showing the significant reduction in winter load variation.

Table 11 also shows that average system loads slightly decrease in the battery cases despite the slight increase in customer loads due to battery round-trip inefficiency. There are two potential reasons for this slight reduction in average load. First, the reduction in peak loads reduces distribution system losses, which are nonlinear in nature. This means that the distribution system has a higher percentage of losses when the system is operating at higher load. Second, the DSO+T annual simulation was executed by running 12-single month simulations. Battery and EV SOC initial conditions were assumed at the start of each month, in part to ensure successful initiation of the simulation. This could lead to batteries receiving a ‘free’ charge at the start of each month. To address this the first three days of simulation were used to initialize performance and establish load behavior independent of initial conditions. The results from the first three days of simulation were not included in the analysis. As will be seen in Section 4.2.1 battery customers do see an annual increase in load. This suggests that the system-level reduction in load is primarily due to reductions in distribution system losses. Finally, as will be seen in Section 3.2, the majority of the economic benefit of a transactive energy implementation comes from peak load reduction, so any impact that the simulation’s SOC initial conditions have on total energy purchases is assumed to be a second-order effect.

Similar, but larger reductions in average load are also seen in the flexible load case. This is due to the combination of reduced HVAC consumption due to slightly higher cooling setpoints and moving operation to periods of colder ambient air temperatures resulting in more efficient cooling system operation combined with reduced distribution losses.

3.1.1.2 Flexible Load Cases

The battery fleet was sized to provide load reduction comparable to that achieved by the flexible loads. This was achieved, with flexible loads showing similar ability as batteries at reducing the peak summer loads (14.2% reduction versus 15.5%) for the high renewable scenario (Figure 42). The HR flexible load case does provide some load modification in the winter (Figure 43), however much of this is achieved by the shifting of EV load from the evening peak. While there is some flexibility provided by HVAC and WH loads, there is insufficient demand for these functions during the midday solar generation peak to allow for significant filling in of the solar ‘duck’ curve. Likewise, few EVs are assumed to be home during the day, limiting the amount of extra EV charging that can be achieved. Furthermore, the EVs that are available for charging during the middle of the day are assumed to charge as soon as possible under the BAU case, limiting the impact of additional early charging of EVs under the transactive cases.

This highlights that flexible loads (EVs, HVAC, WH) are effective resources when their loads align with periods of system constraints (such as peak load). However, they are less effective during periods of time when they are unavailable or have less need and capacity of pre-charging, heating, or cooling. Figure 39 shows this trend, highlighting the ability of flexible loads to reduce system peak loads and daily variation during the summer months, but their diminished capability to reduce the daily variation in system loads during shoulder and winter seasons. This is primarily due to a diminished ability (compared to batteries) to fill the solar ‘duck’ curve during winter and shoulder seasons.

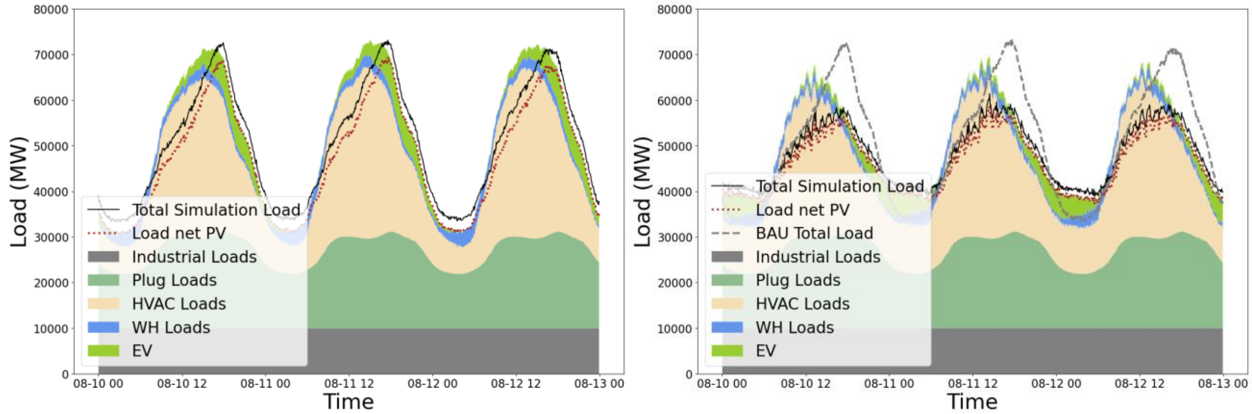


Figure 42. Comparison of BAU (left) and flexible load case (right) load profiles for the HR scenario showing the significant summer peak load reduction.

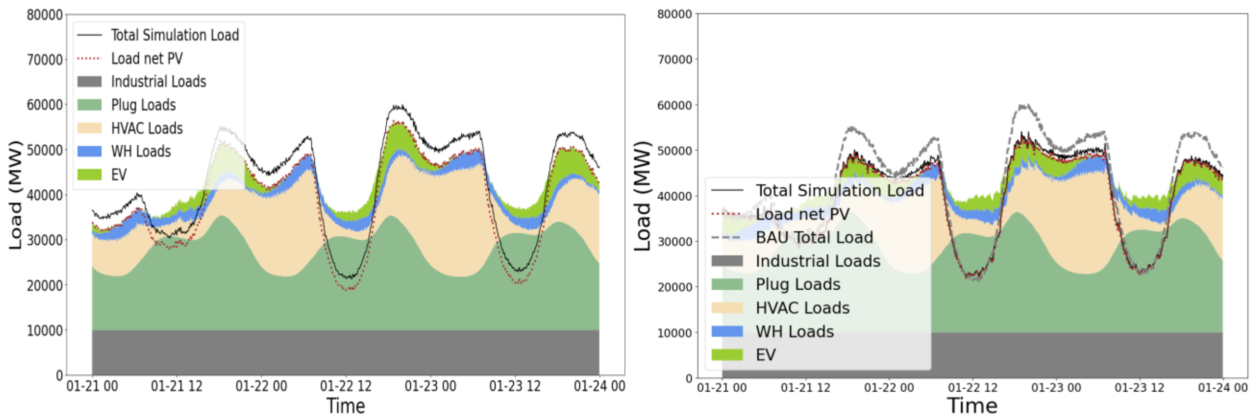


Figure 43. Comparison of BAU (left) and flexible load case (right) load profiles for the HR scenario showing the reduction in winter load variation.

3.1.2 System Generation Impacts

The changes in the system loads presented in the previous section have a direct impact on the resulting system-wide generation requirement and scheduling and dispatch of individual generators. A summary of these impacts are shown in Table 12 and illustrated in Figure 44, Figure 45, and Figure 46. It is important to note that not all changes in the generation dispatch and overall contributions by fuel type may be attributable to the changes in system load. The generation scheduling is based on day-ahead load forecasts that may have small systematic differences between cases. In addition, there may be non-negligible differences in the convergence of solving the unit commitment problem. Furthermore, as was discussed in Section 2.1.4 the simulated wholesale energy market prices do not completely capture the volatility seen in actual ISO markets. This is compounded by the fact that the wind and solar fleet are dispatched outside of the unit commitment problem, preventing an abundance of renewable generation from creating very low or negative wholesale prices. Better simulation of very low or negative wholesale prices in future analysis would result in periods of lower retail transactive rates. This would incentivize flexible loads to shift demand to periods of high renewable output and potentially reduce curtailment.

Finally, the thermal generation fleet was held constant for all cases, as discussed in (Reeve 2022b, Section 2). The economic benefit of requiring less generation (through reduced peak loads) was determined through changes in the generation capacity market price. It is assumed that non-economic generators will not be dispatched. The impact of DER coordination schemes, and the resulting demand flexibility, on system capacity expansion, generator revenue sufficiency, and generator retirement is outside the scope of this study. Despite these caveats, large-scale trends can be identified in the generation results consistent with trends seen in the load profile results.

For the moderate renewable scenario, for the battery case there is a ~1GW (9%) reduction in gas generation, but no appreciable change in generation from nuclear, coal, or wind (see Table 12). This is commensurate with the overall reduction in system load for the MR Battery case (Table 11). The specific reduction in gas generation dispatch may be due to the battery fleet displacing (in small part) the gas generation fleet's role as a ramping and flexibility resource. It may also be due to relatively more expensive gas generators not being dispatched for economic reasons. This trend is increased in the MR Flexible load case which has a slightly lower (4%) average load requirement than the base case and also sees small reductions in wind and coal dispatch.

Table 12. Summary of annual average generation (GW) and share by fuel type and change in absolute generation for the various cases.

	Moderate Renewables					High Renewables				
	Annual Average Gen (GW)			% Change		Annual Average Gen (GW)			% Change	
Fuel	**BAU**	**Batt**	**Flex**	**Batt**	**Flex**	**BAU**	**Batt**	**Flex**	**Batt**	**Flex**
Nuclear	5.1 (12.5%)	5.1 (12.9%)	5.1 (13.4%)	**0.0%**	0.0%	4.7 (11.5%)	5 (11.7%)	5.1 (12.9%)	5.1%	7.8%
Coal	15.6 (38.2%)	15.8 (39.6%)	15.2 (39.6%)	**0.9%**	-2.9%	10.6 (25.8%)	10.5 (24.7%)	9.3 (23.6%)	-1.4%	-12.4%
Natural Gas	14.3 (34.8%)	13 (32.6%)	12.2 (31.8%)	**-9.1%**	-14.4%	9.5 (22.9%)	9.7 (22.9%)	9.1 (23%)	3.0%	-3.8%
Wind	5.9 (14.5%)	5.9 (14.9%)	5.9 (15.2%)	**0.1%**	-1.2%	10.6 (25.7%)	11.3 (26.7%)	10.2 (25.8%)	7.2%	-3.7%
Solar (Utility Scale)	-	-	-	**-**	-	2.4 (5.8%)	2.5 (5.8%)	2.4 (6.1%)	3.4%	0.4%
Solar (Distributed)	-	-	-	-	-	3.4 (8.3%)	3.4 (8%)	3.4 (8.6%)	0.0%	0.0%

The high renewable (HR) scenario sees a doubling of the installed wind capacity (to 32.6 GW) along with the addition of utility scale solar (14.8 GW) and distributed rooftop solar (21.3 GW).

Rooftop solar is not coordinated (curtailed) by either the ISO or the transactive market and is always considered to be dispatched and is therefore identical for all cases.

The effect of DER coordination on the curtailment of wind and solar generation was not the focus of this study. This study did impose a simple curtailment strategy on bulk-system wind and solar to enable solving of the subsequent unit commitment problem. Renewable generators were equally curtailed to ensure there was always sufficient ramping reserve and that there was always more than 8 GW of dispatchable thermal generation in both the MR and HR cases. As a result, the need for curtailment was most prevalent when the total amount of dispatchable thermal generation became small relative to the overall system load. This curtailment limit can be seen in effect in Figure 45. (There is practically no curtailment of wind in the MR cases.)

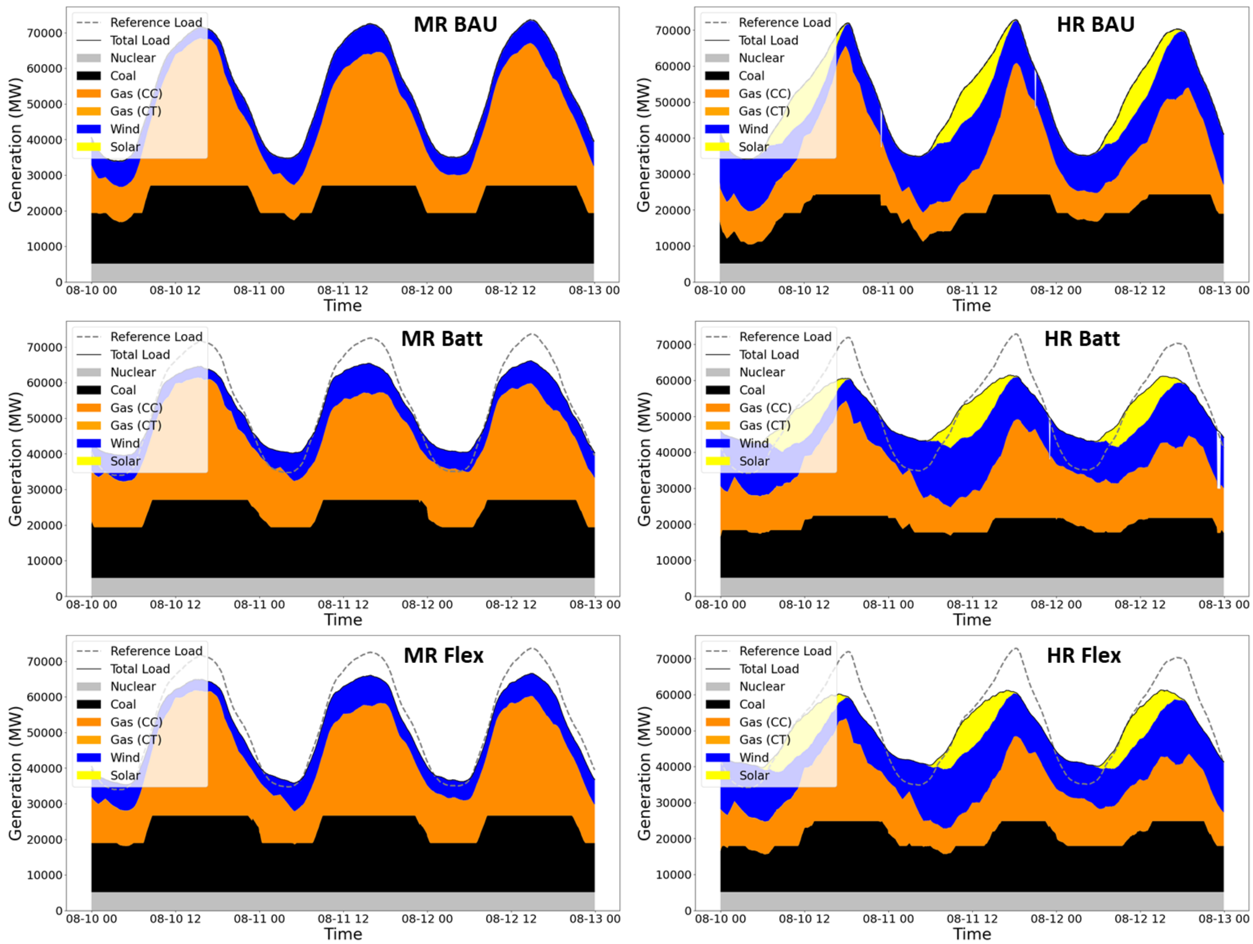


Figure 44. System generation contributions by fuel type for peak demand (summer) showing the moderate renewable (left) and high renewable scenarios (right) and BAU (top), battery (middle), and flexible load cases (bottom). Total generation for each case (solid black line) is shown in comparison to the total generation for the relevant BAU case (dotted grey line).

The high renewable BAU case experienced an 8% curtailment of solar and 10% curtailment of wind. Curtailment typically occurred during daytime hours to address the solar-induced ‘duck’ curve. The batteries in the HR Battery case are incentivized to charge during these daytime hours during winter and spring seasons as shown in Figure 45 and Figure 46. Throughout the year this reduces solar and wind curtailment to 5% and 4% respectively and increases solar generation 3.4% and wind generation 7.2% (Table 12).

Unlike in the battery case, the flexible load case does not appear to be effective at reducing curtailment. This is likely due to two reasons. First, while the HR battery case sees a small increased system load the flexible load case sees a small decrease in system load, decreasing the overall need for generation (Table 11). Second, as discussed in Section 3.1.1.2 flexible loads have a diminished ability to increase loads during daytime hours in the winter and shoulder seasons. While EV and HVAC loads contribute considerable peak load reduction in the summer (Figure 44) they show almost no ability to increase midday loads in the winter and spring (Figure 45 and Figure 46). This is because HVAC service demands are often minimum in the spring and fall, while winter heating loads typically occur at night. In addition, this study assumes that the majority of EVs are not located at charging stations during daytime hours and provide the most opportunity for managed charging during the nighttime hours.

Finally, the HR transactive cases do not see the substantial reduction in gas generation that occurred in the MR transactive cases. The HR flexible load case does see a notable reduction (-12.4%) in coal generation. These trends are likely because even with coordination of DERs there is still a considerable need for system ramping in the HR scenario. This need for system ramping is met by the gas generation fleet, which has higher ramping rates and lower startup costs than the coal generation fleet. Figure 38 and Figure 39 show that while the MR BAU case only experiences large daily changes in load in the summer, the HR BAU case experiences large daily changes in load year-round. This is exacerbated by the presence of utility-scale solar generation that increases the ramping requirement on the thermal generation fleet. Figure 39 shows that batteries and flexible loads can decrease these load swings but are less effective in the winter months.

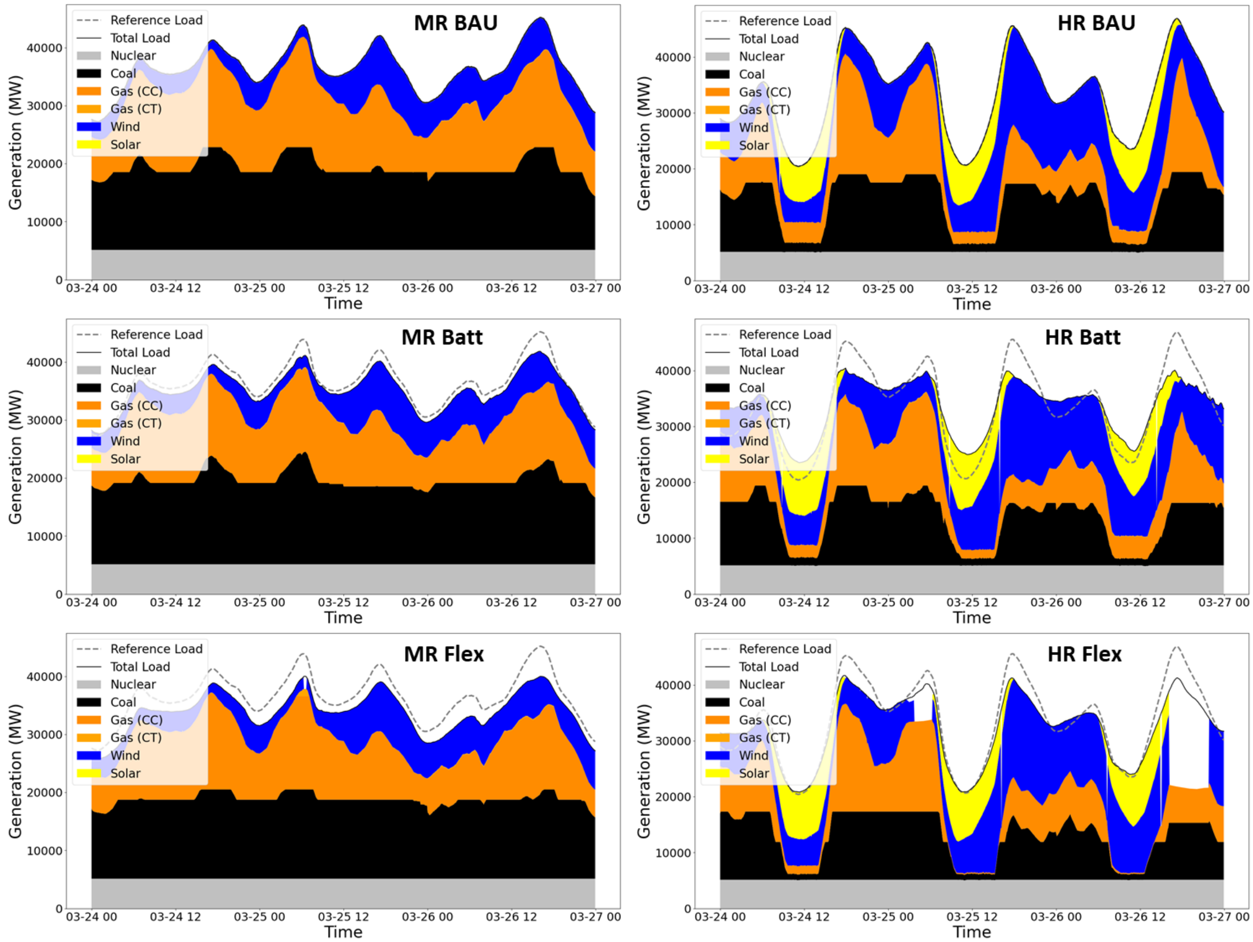


Figure 45. System generation contributions by type for minimum demand (spring) showing the moderate renewable (left) and high renewable scenarios (right) and BAU (top), battery (middle), and flexible load cases (bottom). Total generation for each case (solid black line) is shown in comparison to the total generation for the relevant BAU case (dotted grey line).

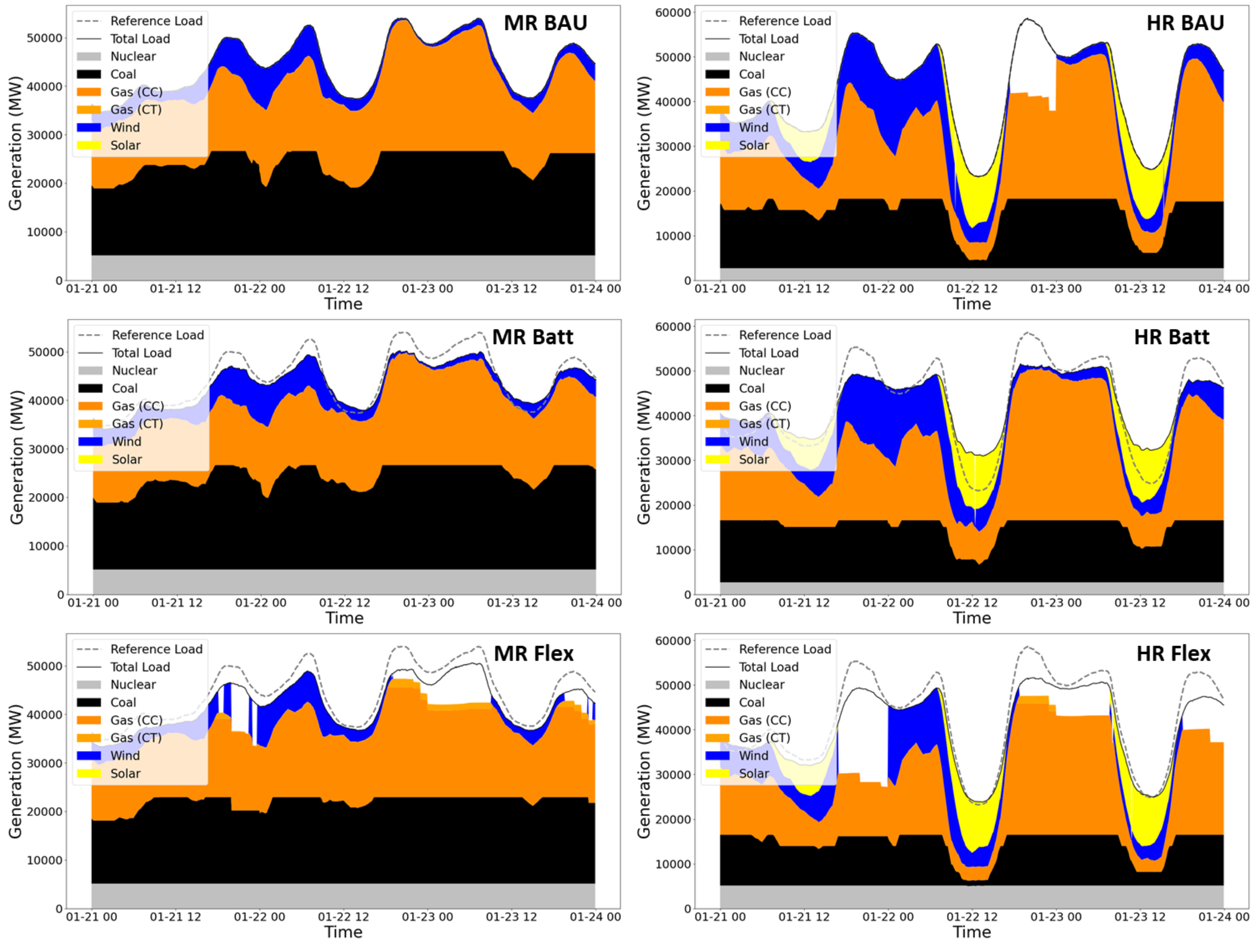


Figure 46. System generation contributions by type for maximum daily load swings in the HR scenario (winter) showing the moderate renewable (left) and high renewable scenarios (right) and BAU (top), battery (middle), and flexible load cases (bottom). Total generation for each case (solid black line) is shown in comparison to the total generation for the relevant BAU case (dotted grey line).

3.1.3 Wholesale Energy Market Impacts

The reduction in peak system loads and diurnal load swings has a commensurate impact on the resulting wholesale energy market prices. Since DSOs purchase the majority of their energy in the day-ahead market,[1] this section will focus primarily on the changes in day-ahead LMPs. A summary of the annual variation and diurnal swings in these values for the MR and HR scenarios are shown in Figure 47 and Figure 48 respectively, and summarized in Table 13.

The MR scenario day-ahead wholesale electricity prices exhibit annual behavior that mirrors the annual load behavior. Higher prices and larger daily variation in price are seen during the peak summer months, with lower prices and variation seen in the winter and shoulder seasons (Figure 47). The transactive cases provide the greatest reduction in price variation during the summer months with smaller but still noticeable reduction in the remainder of the year. Overall,

[1] We are also assuming significant purchases from bilateral markets, which are constant but indexed to average annual day-ahead prices in this study.

the transactive cases reduce annual average daily price variation by ~40-50%. The substantial reduction in daily load variability and price volatility has positive implications on market operation and generator revenue sufficiency. Additional investigation into these aspects is warranted.

Table 13. Summary of annual average and average daily change in day-ahead and real-time LMPs ($/MWh) for each case.

	MR BAU	MR Battery	MR Flex	HR BAU	HR Battery	HR Flex
Day-Ahead LMP: Annual Average	29.19	28.67 (-1.8%)	27.03 (-7.4%)	23.54	25.07 (6.5%)	23.5 (-0.2%)
Day-Ahead LMP: Average Daily Range	29.21	16.59 (-43.2%)	14.72 (-49.6%)	34.61	27.66 (-20.1%)	24.11 (-30.3%)
Real-Time LMP: Annual Average	27.01	26.71 (-1.1%)	29.39 (8.8%)	39.79	24.78 (-37.7%)	31.01 (-22%)
Real-Time LMP: Average Daily Range	22.25	15.39 (-30.8%)	31.08 (39.7%)	179.48	39.77 (-77.8%)	121.7 (-32.2%)

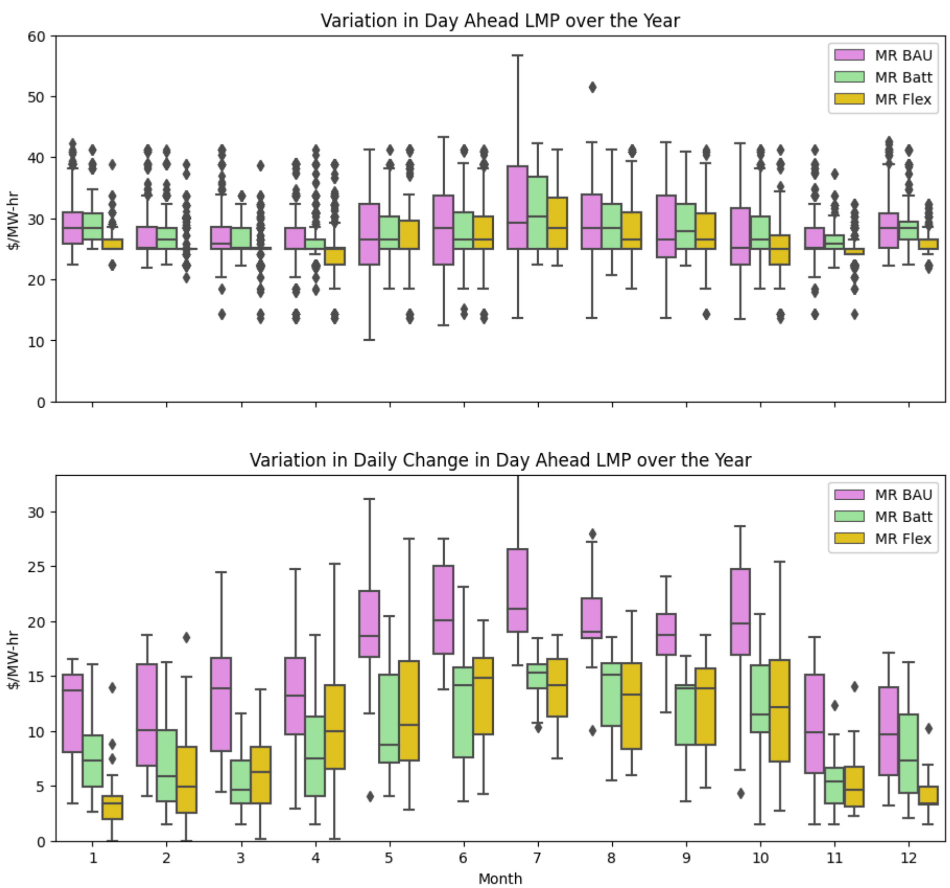


Figure 47. Monthly summary of day-ahead LMP (top) and daily variation in day-ahead LMP (bottom) for the MR scenario.

The annual price trends are less apparent for the HR scenario (Figure 48). This is due in part to increased renewable generation (particularly from solar) creating large daily load variations, and therefore price variations, throughout the year. The transactive cases do reduce annual average daily price variations ~20-30%.

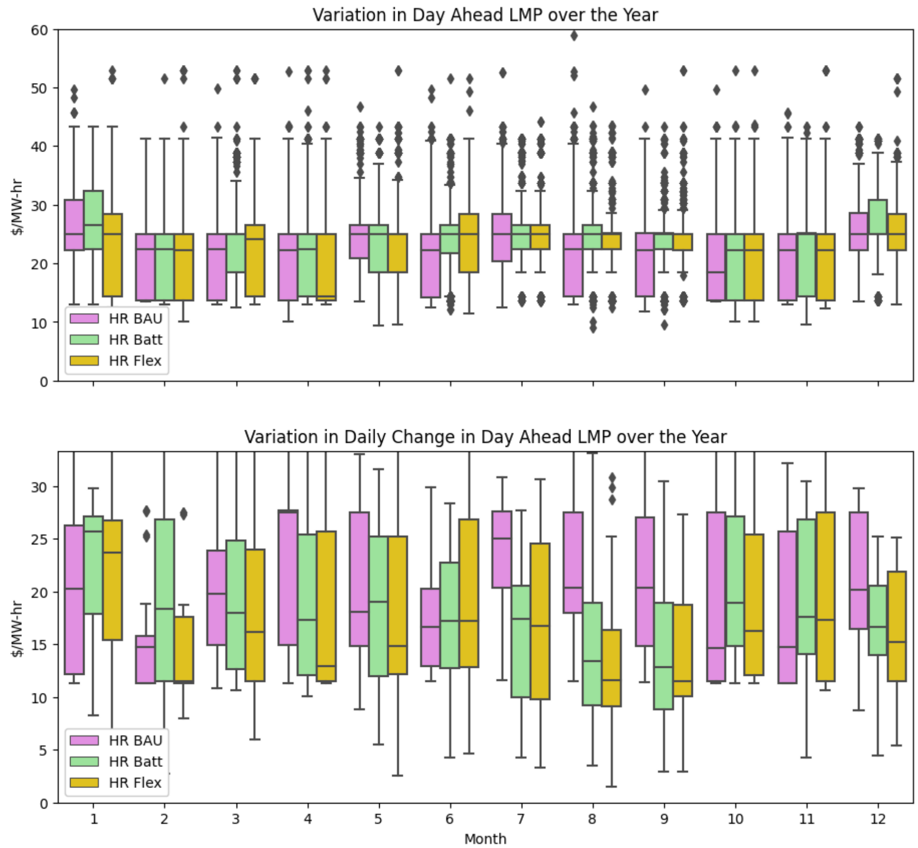


Figure 48. Monthly summary of day-ahead LMP (top) and daily variation in day-ahead LMP (bottom) for the HR scenario.

While the average prices drop for most transactive cases (due to the decrease in peak loads and slight decrease in average loads) the average day-ahead price increases for the HR battery case. This is attributed to differences in load forecast accuracy between the cases, as the day-ahead price is based on the DSO's forecast day-ahead load, not the actual load. If one case has a slight forecast error bias, it will result in day-ahead purchases that are higher or lower than the other cases. This is mitigated in part by the real-time market that is used to reconcile and correct the bid day-ahead quantities. That is, if a DSO overpredicts its day-ahead quantity, the excess will be sold in the real-time market and the DSO will be credited the difference. Even with the increased annual average day-ahead price, the HR battery case sees a 37% reduction in real-time prices and an overall 4.6% reduction in wholesale energy purchase expenses. This is due in part to the real-time market correction, as well as the fact that battery operation results in the DSO purchasing more electricity during periods of lower prices and less during peak prices.

Table 13 also summarizes the average annual real-time LMP statistics for each case. The MR flexible load case is the only case that does not reduce average real-time LMPs and daily variation in LMP. This may be due to relative underprediction of the flexible loads' quantity. The HR BAU case sees substantially higher average real-time LMPs and daily variation. This may be caused by the increased variability of the higher penetration of renewable energy resulting in greater variability in the real-time market. Market operation at these high levels of renewables, as well as the role that the accuracy of price forecasts and flexibility estimates play in the formation of day-ahead and real-time prices warrants additional research.

3.2 Resulting Annualized Cash Flow Impacts

The simulation results (in particular, peak system loads and energy market purchases) are key inputs into the economic analysis that determines changes in annualized cash flow by stakeholder. The waterfall chart in Figure 49 shows a summary of the changes in annualized cash flow between the BAU and transactive cases for the MR and HR scenarios. Left-to-right Figure 49 cumulatively adds the impacts of the wholesale system costs (capacity payments, energy purchases, transmission costs, and ancillary services), distribution system costs (distribution hardware capital costs, O&M and labor costs, information technology and software costs, and workspace costs), and customer borne costs (investments to acquire and upgrade DER assets).

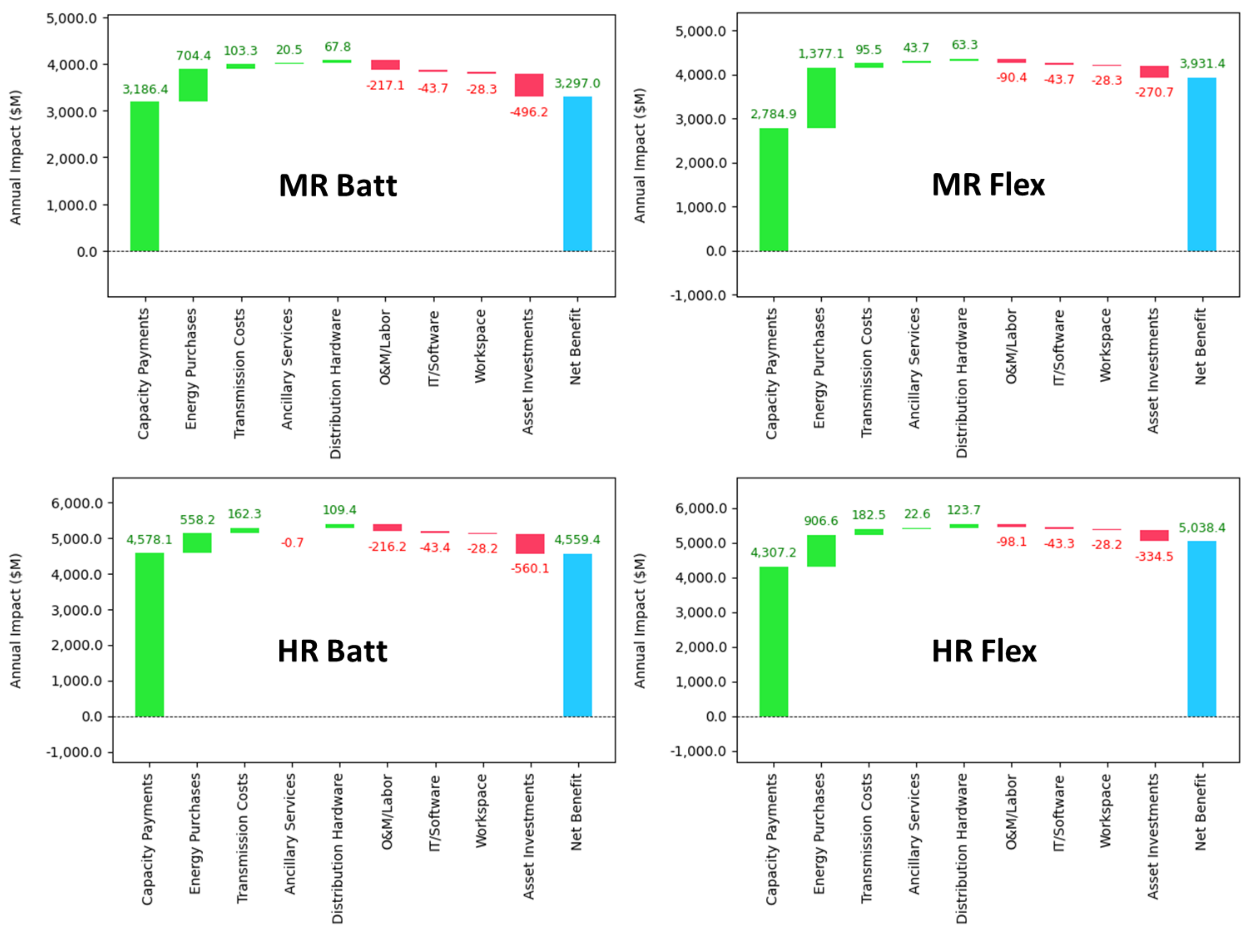


Figure 49. Summary of changes in annualized cash flow between the BAU and transactive cases showing economic benefits and costs of implementation for both the MR and HR scenarios.

The primary benefit of a DSO+T implementation is due to the reduction in system peak load and, in particular, as reflected in a DSO's required generation capacity payments. Peak load reduction not only lessens the quantity of generation capacity that must be procured in a capacity market, but also substantially reduces the resulting auction price for this capacity. It is this second attribute that results in large savings. This study assumes that a 1% reduction in required capacity lowers the capacity price 5% consistent with other studies (Pratt et al. 2022, Section 3.3.1.3). All cases see a substantial reduction in capacity market costs, with larger savings in the HR cases due to the additional flexibility and peak load reduction provided by managed charging of the EV fleet. It should be noted that almost all cases would still see a net cost benefit even if there were no capacity market savings. The HR battery case would see a negligible $19M/year cost increase (0.06% of annual operating expenses) – essentially cost neutral in the absence of capacity market savings.

The reduction in peak load also saves in transmission and distribution costs resulting from the deferral of growth-driven capital investments in this infrastructure. These benefits have been calculated for general growth rates and transmission and distribution system designs. Actual benefits will be dependent on the actual load growth rates and system constraints seen on an operator's system.

There are also wholesale market benefits from savings in the purchases of energy. These savings are due to the reduction in peak loads (and therefore not having to dispatch expensive generation) that results in lower average prices. More importantly, however, is the fact that flexible assets shift more of their consumption to periods of lower prices. So, while for the MR battery case average prices dropped 1.8%, energy purchase costs dropped 7.3%. The flexible load cases saw greater energy market savings due to their overall reduced amount of energy purchased.

The impact of ancillary services was not found to be a significant target for economic benefit in this study. This is because ancillary services represent <3% of total cost of electricity and we assume no change in their price as they are purchased based on the total energy volume (which varies by only a few percent between cases). Demand flexibility may significantly mitigate the increased need for ancillary services associated with increased load and generation variability in the future. These direct benefits may warrant further investigation.

The costs to implement a transactive retail market as well as the flexible assets are borne by the DSOs and customers. DSO labor is increased due to the personnel needed to run the retail marketplace, additional AMI operations capability, and strengthened retail operations. This increase in employee headcount results in a small increase in workspace costs. Software costs are also estimated to increase due to the implementation of a retail marketplace, integration into the existing distribution management system, and the required DER communications network. Finally, we are assuming that the cost to implement or upgrade flexible assets is borne by the customer and captured in their annualized cash flow.

The net result of these wholesale and capital infrastructure benefits combined with DSO and customer implementation costs is an annualized benefit of $3.3B for the MR battery case. This is representative of the nominal net benefit for all cases that ranged from $3.3B to $5.0B as shown in Figure 50. The flexible load cases achieve slightly lower peak load reductions and therefore have reduced savings in capacity payment, transmission, and distribution expenses. This is more than offset by increases in energy purchase savings as well as lower asset investment costs. For flexible loads, customers only pay the incremental cost to implement smart controls and connectivity on existing devices to enable participation. For the battery case we assume the full battery system investment cost (assuming aggressive battery cost reductions) to attributable to transactive participation. The region wide difference in asset investment costs between the MR battery and MR flexible loads case is $226M/year. Figure 50.

also shows the expected net benefit under both high and low capacity market price assumptions. These assumptions and other sensitivity analysis are discussed in the next section.

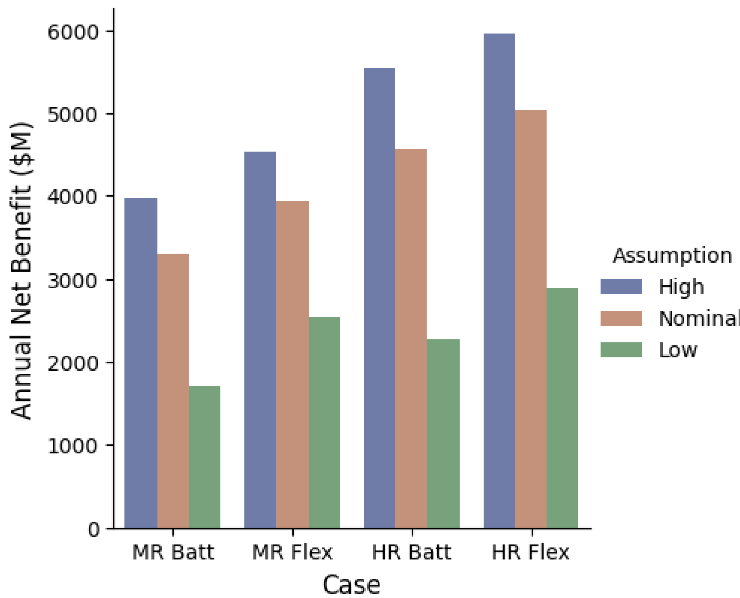


Figure 50. Summary of annualized net benefit to customers for each case under high, nominal and low capacity price assumptions.

3.2.1 Sensitivity Analysis

The range of results shown in Figure 50. are based on an economic sensitivity analysis using a range of capacity market assumptions. Future capacity market prices will likely be driven by the addition of renewable generation (which may suppress capacity market prices), load growth due to electrification of space heating and transportation, and growing needs for resource adequacy for extreme events. Both these needs will tend to increase the demand for new generation and potentially increase capacity market prices. For this study, the nominal analysis assumed a capacity market price of $75/kW-year for the BAU case based on an examination of reported U.S. capacity market prices over time (Jenkin et al. 2016). This study also applied a quantity-price sensitivity factor to capture the nontrivial impact that reducing the required capacity has on the cleared capacity market price. We assumed a sensitivity factor of 5 based a range of reported sensitivities (Jenkin et al. 2016; Bowring 2013). These assumptions are identical to the values used in the Grid-Interactive Efficient Buildings Roadmap value analysis for their ‘High Capacity Value’ case (DOE 2021). For the low capacity price case we assumed a halving of the capacity cost ($37.5/MWh). This is at the lower end of almost all the regions for which 2030 average generation capacity cost was calculated (DOE 2021, Figure 23). For the ‘high’ capacity price assumption we used a capacity value of $91/kW-yr to reflect the full annualized cost of a peaker plant. Even assuming a low capacity market price the net benefit was $1.7-2.9B. Full documentation of the capacity price assumptions is provided in Volume 4, Section 3.3.1.3 (Pratt et al. 2022).

The overall system benefits are less sensitive to other key assumptions. Analysis of the transmission infrastructure cost basis determined a capital cost of $169/kW (Pratt et al. 2022). Based on the calculated annual cost of capital of 8.25%, this results in an annual cost of transmission infrastructure of $13.9/kW-year. This agrees well with the avoided cost of transmission ($15/kW-year) used in DOE (2021). This does, however, assume that there is a one-to-one relationship between reduction in system peak load and required transmission infrastructure. In a complex mesh-network transmission system design this assumption may not hold. If load reduction is assumed to only result in a 50% reduction in transmission system infrastructure deferral, the overall benefits would be reduced by $48-91M/yr.

We consider the calculated energy purchases cost reduction to likely underestimate the actual savings. This is because the DSO+T simulation does not replicate the infrequent but large deviations in day-ahead and real-time LMPs. For 2016, ERCOT experienced day-ahead LMPs above $40/MWh approximately 8% of the time, accounting for 27% of annual purchases if all load was bought at day-ahead prices; however, in the simulation, prices only occurred above $40/MWh 4.5% of the time and accounted for 9% of energy market costs. This suggests that the simulation is underpredicting the benefit of reducing energy consumption during periods of high prices. However, when 2016 ERCOT day-ahead LMP prices are used with simulation load profiles (without assuming any elasticity in prices with loads), the energy purchases benefit is only slightly larger (7%). This suggests that the simulation is capturing the overall trends in wholesale energy cost benefits but the value of lowering extreme prices warrants further investigation. The study results were considered insensitive to the cost of ancillary services, so these were not included in the sensitivity analysis.

Finally, doubling select implementation costs does not substantially alter the overall system benefit. For example, doubling the DSO implementation costs, including required labor for AMI network operation, cybersecurity, and retail operations as well as the software costs associated with the retail market and DER network would decrease the overall benefits $150-240M/yr. In terms of customer implementation costs, the main uncertainty is in future battery implementation costs. A doubling of battery implementation costs would reduce the overall benefits approximately $0.5B/yr. Since all other customer implementation costs (i.e., smart chargers and thermostats) were based on available products, it was assumed these would only further decrease in price when deployed at scale.

4.0 Customer Results

This section presents results from the customer population perspective. It starts by detailing BAU results for the moderate and high renewable scenarios to describe the energy and cost patterns seen by customer type. It then presents the energy and cost impacts associated with the transactive cases.

4.1 Business-as-Usual Customer Performance

This section presents the energy consumption, peak load, and electric bills across the customer population for the business-as-usual cases. These comparisons of customer metrics are enabled by modeling the individual characteristics and performance of tens of thousands of customer buildings. The distributions in building size, insulation levels, operating schedule, and equipment performance result in variations in annual energy consumption and electric bills across the customer population. This section will focus on residential buildings as a larger number of these buildings were simulated and they have a smaller variation in building size, more clearly demonstrating key trends.

4.1.1 Moderate Renewable Scenario

The energy consumption of residential customers in the moderate renewable scenario is primarily a function of building type, heating type, and size. The simulation results show that residential customers in multifamily housing (i.e., apartment buildings) have lower annual energy consumption and electric bills than manufactured or single-family detached homes (Figure 51). This is due, primarily, to the smaller size and reduced exterior envelope area per housing unit and, therefore, heat transfer with the outside. This reduces the required space air conditioning load and the annual electricity consumption. Multifamily units also show lower peak loads, although this data is multi-modal suggesting that this varies by DSO, likely due to climate conditions.

Similar trends are seen for building heating type (Figure 52). Buildings with gas heat pay less in electric bills than customers with heat pumps or resistance heat, due to the eliminated electric space and water heating electricity consumption. Residences with heat pumps show lower energy consumption and costs than electric resistance homes due to the high efficiency of heat pumps. This behavior matches expected trends and illustrates the granularity achievable from the simulation given the customer attributes and population size. A summary of average energy metrics by building and heating type are shown in Table 14.

These categorical trends are consistent with the trends seen in building parameters that are continuous. For example, Figure 53 shows that, as expected, energy consumption increases as a function of building size (square footage) illustrating the larger size of single-family homes and the associated increased energy consumption.

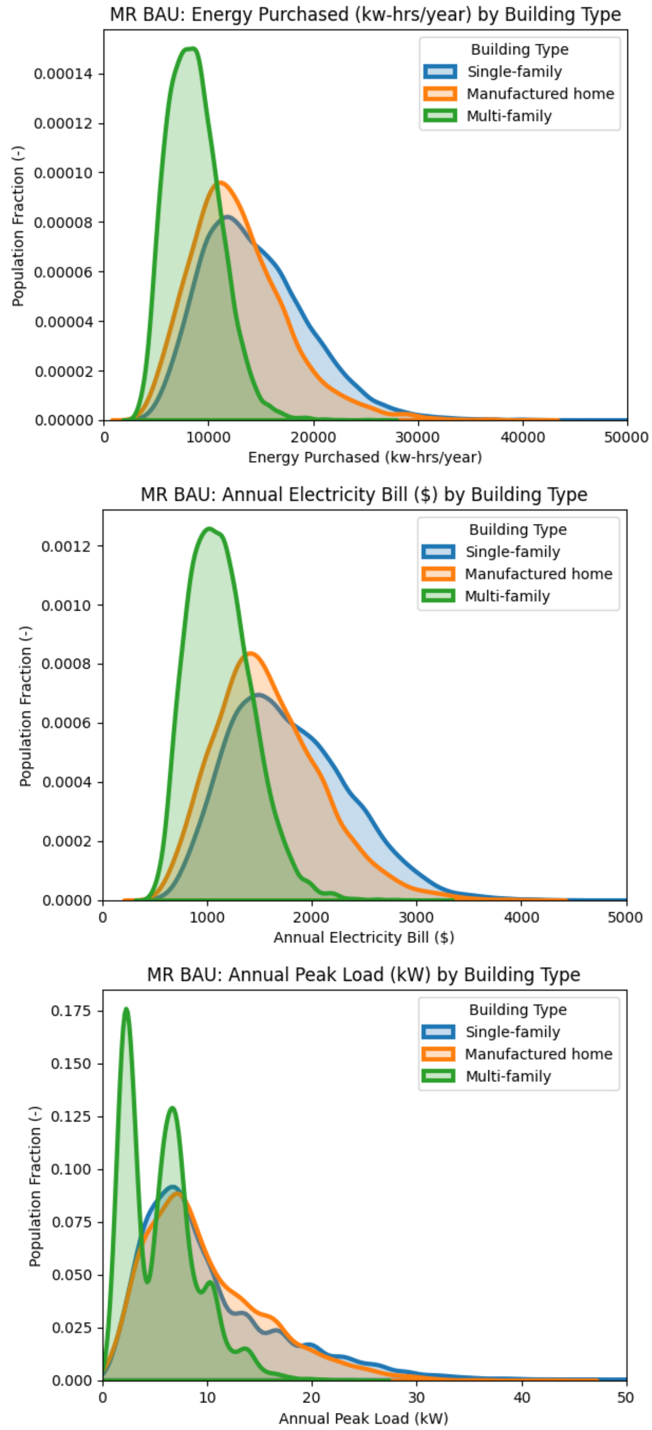


Figure 51. Impact of residential building type on customers' annual energy consumption (top), electricity bills (middle), and peak load (bottom) for the MR BAU case.

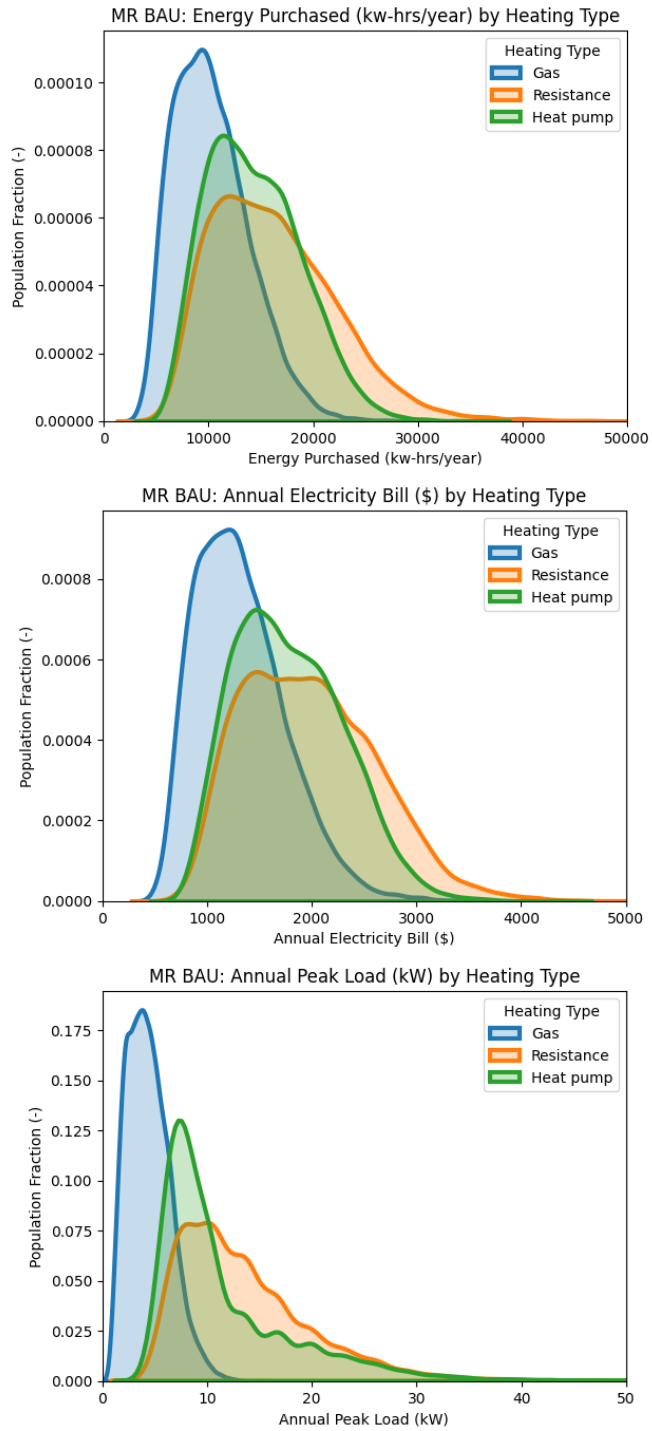


Figure 52. Impact of residential heating system type on customers' annual energy consumption (top), electricity bills (middle), and peak load (bottom) for the MR BAU case.

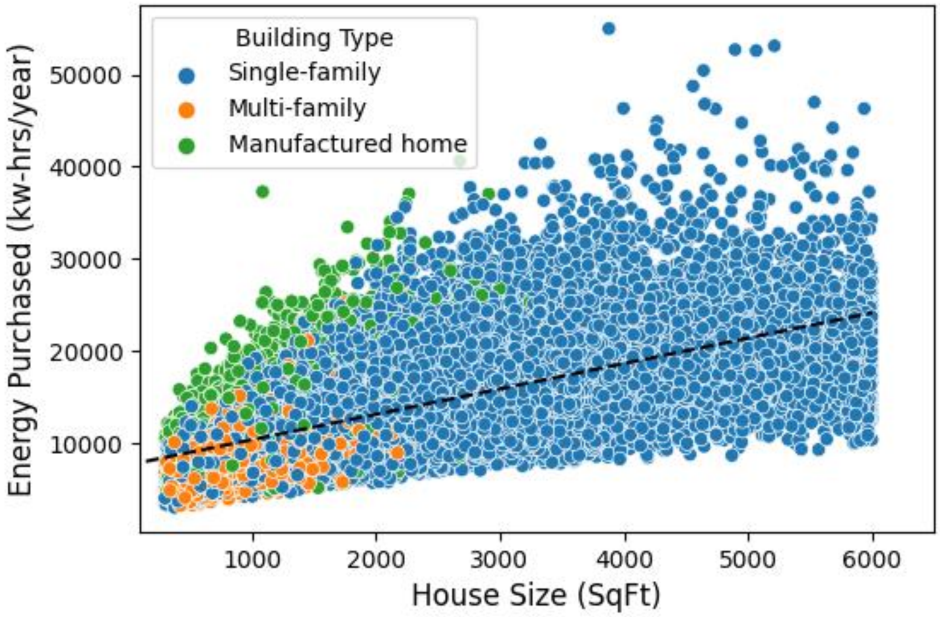


Figure 53. Impact of residential building size on annual electricity consumption.

Table 14. Summary of metrics for average residential customers by building and heating type (MR BAU case).

Metric	All Residential	Single-Family	Multifamily	Manufactured
Annual Energy (kW-hrs)	13340	14450 (8.4%)	8620 (-35.4%)	12850 (-3.6%)
Peak Load (kW)	9.4	10.2 (8.6%)	5.7 (-39.9%)	9.8 (3.9%)
Annual Utility Bill ($)	1660	1790 (7.7%)	1130 (-32.1%)	1590 (-4.2%)
	All Residential	Gas	Heat Pump	Resistance
Annual Energy (kW-hrs)	13340	10420 (-22%)	14350 (8%)	16410 (23%)
Peak Load (kW)	9.4	4.5 (-52%)	11.6 (23%)	13.5 (43%)
Annual Utility Bill ($)	1660	1340 (-20%)	1790 (7%)	1990 (20%)

4.1.2 High Renewable Scenario

The high renewable scenario assumes the same customer population and building parameters as the moderate renewable scenario, but randomly assigns some customers rooftop solar and electric vehicles. The impact of rooftop solar power generation and EV charging is additive to the building loads presented in the previous section. As shown in Figure 54 and Table 15, EV ownership increases annual energy consumption and annual electrical bills ~45-50% while PV ownership lowers net energy consumption and electric bills >30%. As expected, EV ownership increases the annual household peak load 6.7 kW (>70%). The simulation does not show PV ownership providing any substantial reduction in customer peak load.

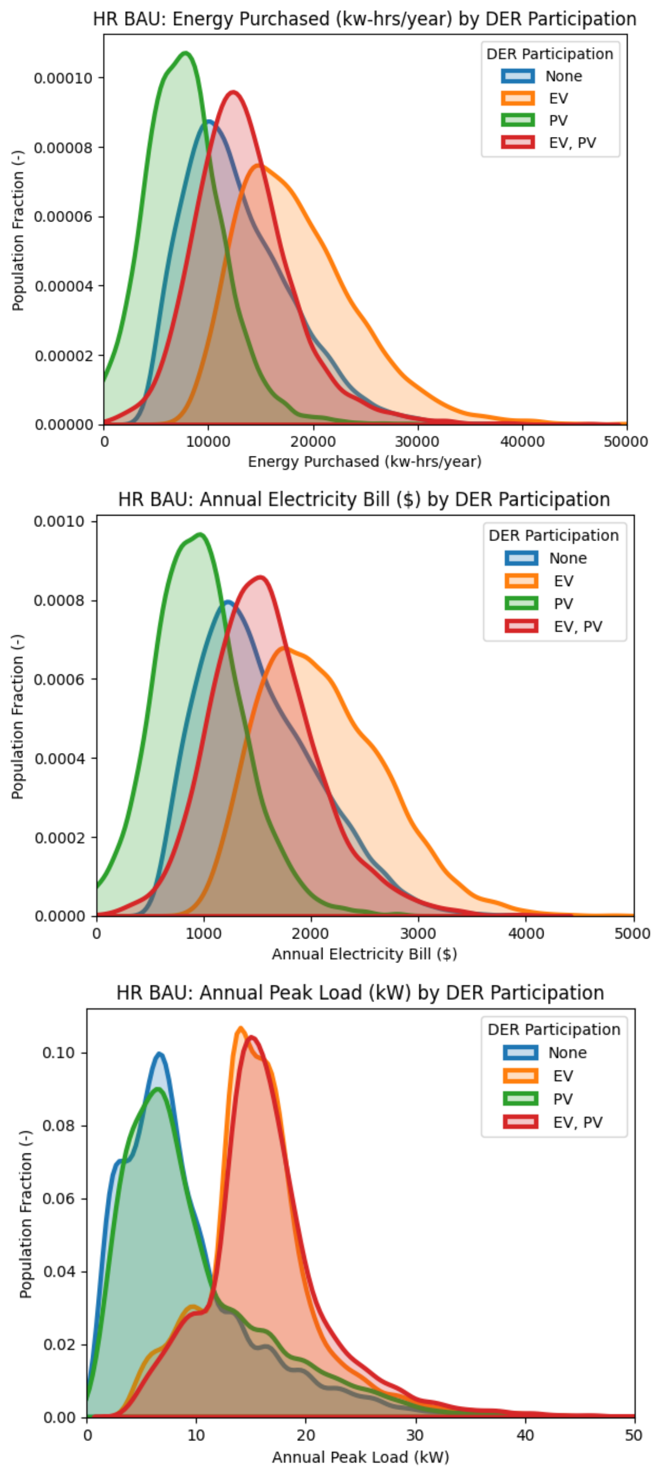


Figure 54. Impact of PV and EV ownership on customers’ annual energy consumption (top), electricity bills (middle), and peak load (bottom) for the HR BAU case.

Table 15. Impact of EV and PV ownership on key energy metrics of residential customers in the HR BAU case.

Metric	All Residential	Without PV	With PV	Without EV	With EV
Annual Energy (kW-hrs)	12,970	14,560	9290 (-36.1%)	11,260	16,960 (50.6%)
Peak Load (kW)	11.3	11.1	11.9 (7.5%)	9.3	16 (72.7%)
Annual Utility Bill ($)	1,530	1,700	1,130 (-33.2%)	1,350	1,950 (44.9%)

4.2 Transactive Energy Results

This section discusses the impact that DER flexibility has on customers' energy consumption, peak loads, and energy costs. The focus of this section will primarily be on comparing residential participating and nonparticipating customers. Annual results are shown comparing the results of the battery case versus flexible load case and how bill impacts are distributed throughout the year. The section also includes comparisons between residential and commercial customers, the impact of slider setting (level of participation) on customer savings, and how types of building, DSO, and DER impact customer savings.

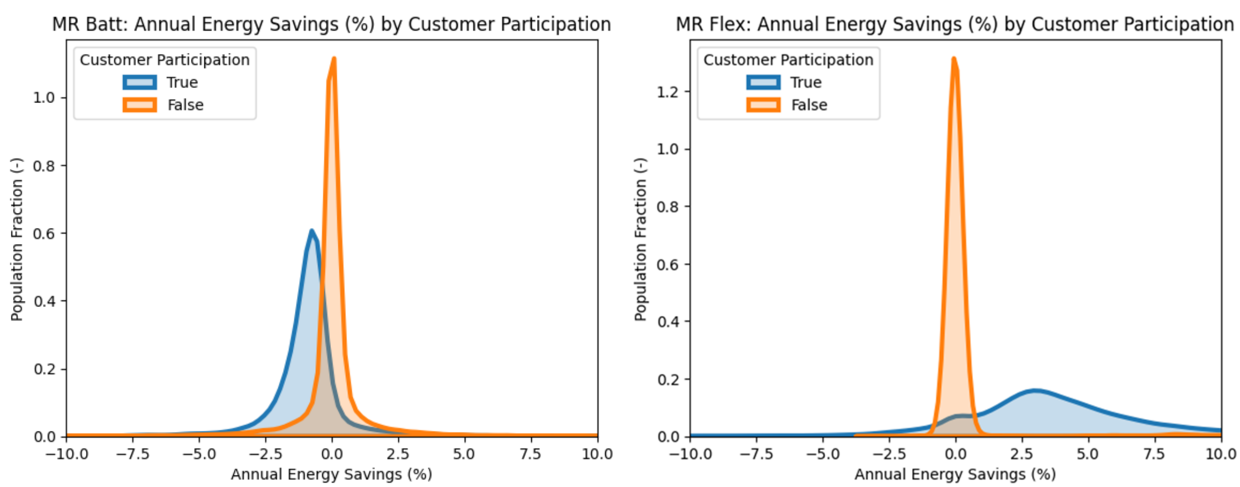


Figure 55. Change in annual energy consumption for participating and nonparticipating residential customers for the MR battery (left) and MR flexible load (right) cases.

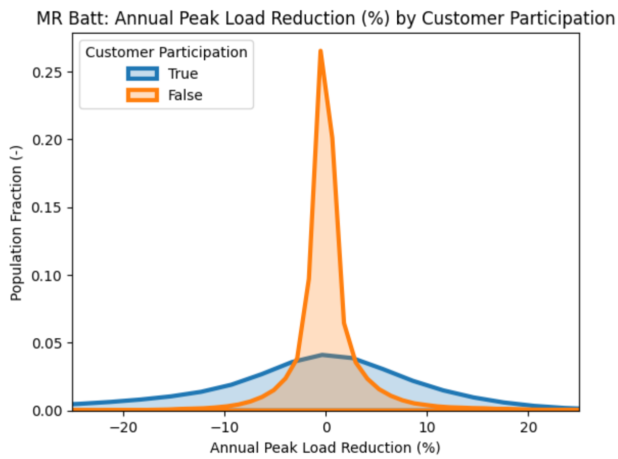
4.2.1 Customer Savings for Battery and Flexible Load Cases

Figure 55 shows the percent change in annual energy savings for both participating and nonparticipating residential customers[1]. In the battery case participating residential customers consume slightly more energy (0.8%) over the course of the year due to the round-trip efficiency of the battery. Non-participating customers see no change in energy consumption, as expected. In the flexible loads case, the operation of HVAC units with setback thermostat schedules and operating precooling/preheating (often at more efficient outdoor air temperatures) reduces the average participating residential customer's energy consumption 4.4%. The energy

[1] Note that all simulated customers across the 40 DSOs (in this case 58,500 residential customers) are shown in this and subsequent figures. Customer distributions are not scaled by the weighting factor of each DSO. This ensures trends in smaller (mostly rural) DSOs are visible.

consumption of nonparticipating customers is still practically unchanged (within 0.3% of the BAU case) demonstrating the consistency in results between simulations.

On average residential customers' annual peak load did not substantially decrease (Figure 56). This is initially surprising given that the MR scenario cases saw coincident system peak load reductions of 9-10%. This is because the transactive coordination scheme incentivizes load reduction during periods of high energy prices and distribution-level delivery constraints. The resulting demand flexibility and load shifting can result in peak loads occurring at other times of the day. In fact, several DSOs switched from summer to winter peaking when the transactive retail market was implemented. Figure 56 plots the change in a customer's 15-minute peak annual load (on which demand charges are based for commercial and industrial customers on the fixed tariff). This suggests that the monthly demand peaks of many customers do not align with the system coincident peak, or that demand flexibility effectively moves these peaks to other, non-coincident, times.



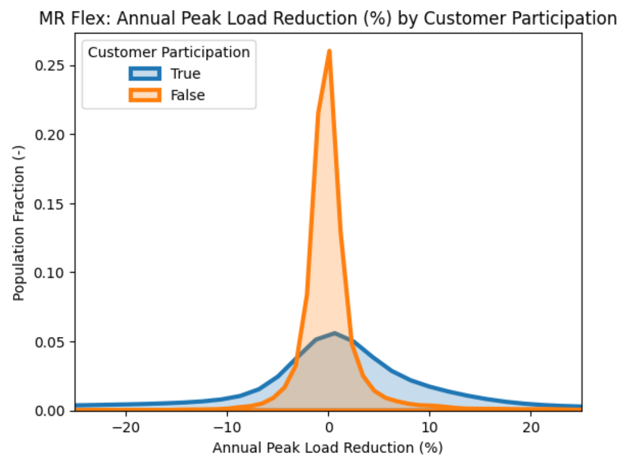


Figure 56. Change in annual peak load for participating and nonparticipating residential customers for the MR battery (left) and MR flexible load cases (right).

The changes in individual customers' annual energy profile, consumption, and peak loads impact the DSO's expenses (as discussed in Section 3.2) and required revenue recovery. This ultimately impacts the customer's annual utility bill. The annual utility bill savings for participating and nonparticipating residential customers is shown in Figure 57 for all DSOs in the MR scenario[1]. Participating residential customers experience similar annual savings for the battery and flexible load cases (14% and 17% respectively for the MR scenario). Of significant importance is the fact that nonparticipating customers save on their average annual utility bill and practically all customers see a reduction in their bills. Nonparticipating customers see an average reduction (of ~10%) in utility bills because their fixed rate tariff is designed to recover revenue equivalent to what would have been collected under the dynamic transactive rate. This ensures that nonparticipating customers also benefit from the reduced overall cost basis of their

[1] Note that the customer probability distributions of utility bill savings are multi-modal due to customer savings being primarily driven by the savings of each of the 40 DSOs that comprise the population of the entire region. This is exasperated in the flexible load case as the non-participating customer base is only ~20% of the entire population and the resulting required rate recovery and fixed tariff from this smaller simulated customer base can be influence by a few customers (particularly large commercial customers). While showing results for only one DSO eliminates the multi-modal nature of the results, we chose to show the largest possible representation of the simulated population.

DSO. However, participating customers do, on average, experience larger savings. This confirms an important rate design principle: that customers who participate and provide flexibility achieve higher savings than those who do not.

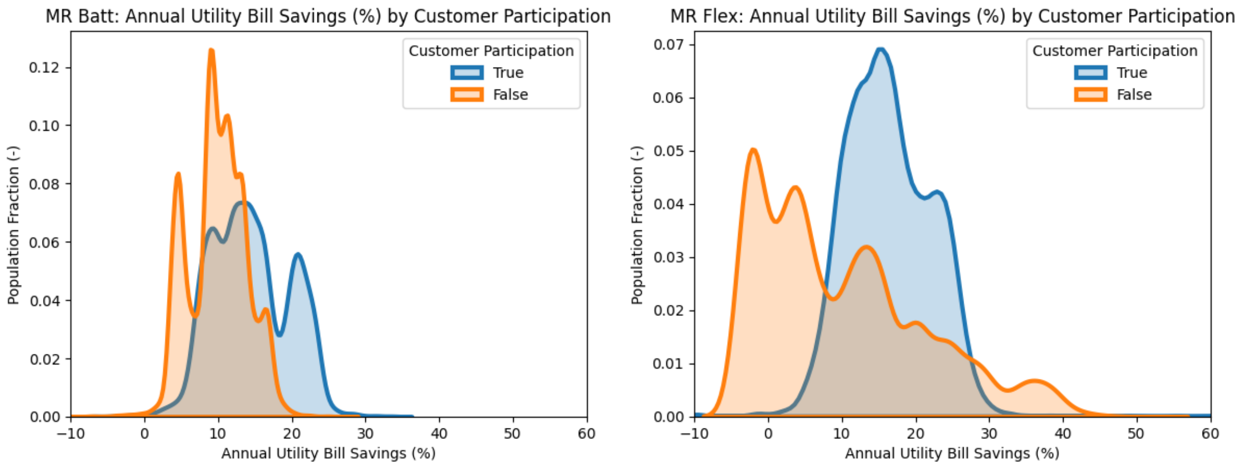


Figure 57. Change in annual utility bill payments for participating and nonparticipating residential customers for the MR battery (left) and MR flexible load cases (right).

A customer's annual utility bill savings is offset by the annualized expense of any flexible asset installation and operation. The net result is the total savings in annual customer energy expenses, as shown in Figure 58. For the battery case the annualized cost of installing and operating the system can result in negative overall savings for a small portion of customers, especially customers who configure their devices to provide limited flexibility. More importantly, the resulting annual net energy expense benefit becomes lower for participating customers versus nonparticipating customers (8% versus 10%). This may be acceptable to participating customers given the additional value propositions of battery ownership (e.g., back-up power and self-consumption of onsite renewable generation). The flexible load case does not see such a large reduction in overall benefits due to the much smaller flexible asset investment expense associated with installing smart thermostats and water heater controllers. A summary of the key residential customer metrics is provided in Table 16.

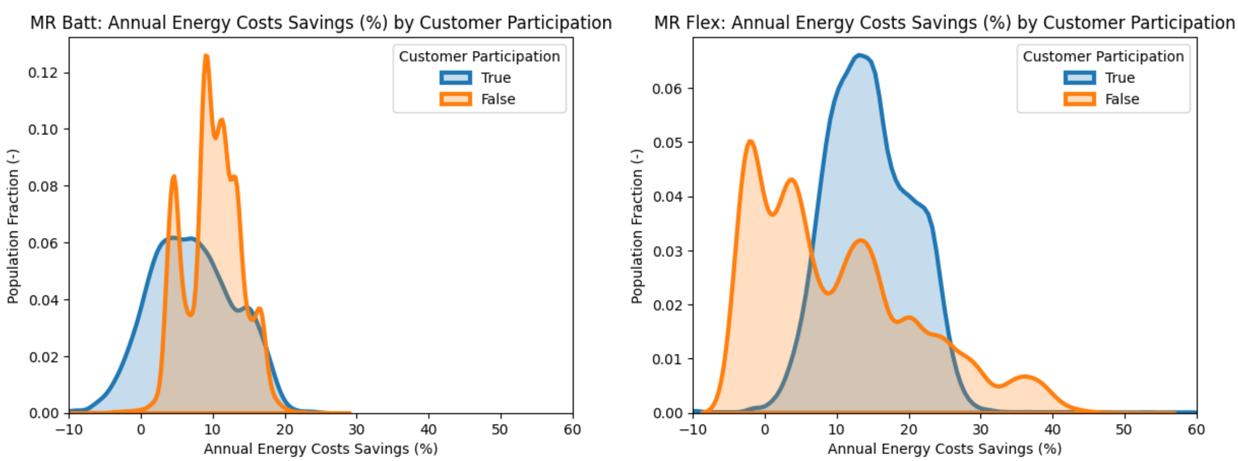


Figure 58. Change in total annual energy expenses for participating and nonparticipating residential customers for the MR battery (left) and MR flexible load cases (right).

Table 16 also includes key residential customer metrics for the HR scenario. In this scenario there are similar small changes in annual energy consumption and an increase in peak load by participating customers. In the HR flexible load case participants see a smaller benefit over nonparticipating customers than in the MR flexible load case. This is due to flexible asset costs including EV smart charging for the fraction of customers with EVs. In addition, since 40% of customers have rooftop solar the annual net energy consumption and electric bill is lower, resulting in the investment costs of flexible assets becoming a larger fraction of bill savings. The impact of flexible asset type and rooftop solar on customer benefits is discussed more in Section 4.2.4.

Table 16. Summary of metrics for average participating and nonparticipating residential customers.

Metric	MR Flexible Loads		MR Battery	
	Nonparticipating	Participating	Nonparticipating	Participating
Annual Energy (kWh)	13,340 (-0.3%)	12,740 (-4.4%)	13,330 (0%)	13,460 (0.8%)
Peak Load (kW)	9.4 (-0.5%)	9.5 (1.2%)	9.4 (-0.5%)	9.6 (1.2%)
Annual Utility Bill ($)	1,500 (-10.2%)	1,390 (-16.6%)	1,500 (-10.1%)	1,430 (-14.2%)
Annual Energy Expenses ($)	1,500 (-10.2%)	1,420 (-14.8%)	1,500 (-10.1%)	1,540 (-7.8%)
	HR Flexible Loads		HR Battery	
	Nonparticipating	Participating	Nonparticipating	Participating
Annual Energy (kWh)	11,270 (-0.3%)	12,680 (-4%)	11,260 (0%)	14,260 (0.4%)
Peak Load (kW)	9.3 (0.2%)	10.2 (-12.3%)	9.3 (0.2%)	11.6 (-8.7%)
Annual Utility Bill ($)	1,170 (-13.6%)	1,290 (-16.6%)	1,190 (-11.2%)	1,390 (-15.9%)
Annual Energy Expenses ($)	1,680 (-9.9%)	1,850 (-10.8%)	1,710 (-8.1%)	2,000 (-8.2%)

Table 17. Summary of metrics for average participating and nonparticipating commercial customers.

Metric	MR Flexible Loads		MR Battery	
	Nonparticipating	Participating	Nonparticipating	Participating
Annual Energy (kWh)	149,720 (-0.5%)	140,760 (-2.5%)	147,460 (0.1%)	142,980 (0.2%)
Peak Load (kW)	47 (0.2%)	45 (-3.8%)	47 (0.2%)	45 (-1.4%)
Annual Utility Bill ($)	15,520 (-8.9%)	13,950 (-15.7%)	15,030 (-10.6%)	14,040 (-14.3%)
Annual Energy Expenses ($)	11,940 (-8.9%)	10,870 (-15.1%)	11,640 (-10.6%)	10,980 (-13.1%)
	HR Flexible Loads		HR Battery	
	Nonparticipating	Participating	Nonparticipating	Participating
Annual Energy (kWh)	142,100 (-0.6%)	130,360 (-2.4%)	134,670 (0%)	135,060 (0.1%)
Peak Load (kW)	46 (0.1%)	44 (-5.3%)	45 (0%)	45 (-3.8%)
Annual Utility Bill ($)	13,460 (-10.9%)	11,720 (-20.4%)	12,920 (-11.2%)	11,970 (-19.9%)
Annual Energy Expenses ($)	12,080 (-9.5%)	11,000 (-17.1%)	11,830 (-9.7%)	11,210 (-16.3%)

A comparison of the annual total energy expenses between participating residential and commercial customers is shown in Figure 59. The commercial customer population exhibits a greater range in benefits and a more substantial portion of customers who see an increase in annual energy costs. These trends are likely due to two reasons. First, some commercial customers likely experience much higher savings due to the elimination of the demand charge. Second, there is likely more variation in the load profiles of the commercial building fleet, resulting in a larger variation in the impact of customers switching to a dynamic rate structure that more closely reflects the cost of electricity sold. Even with these effects the average reduction in annual energy expenses is similar between commercial (Table 17) and residential customers (Table 16).

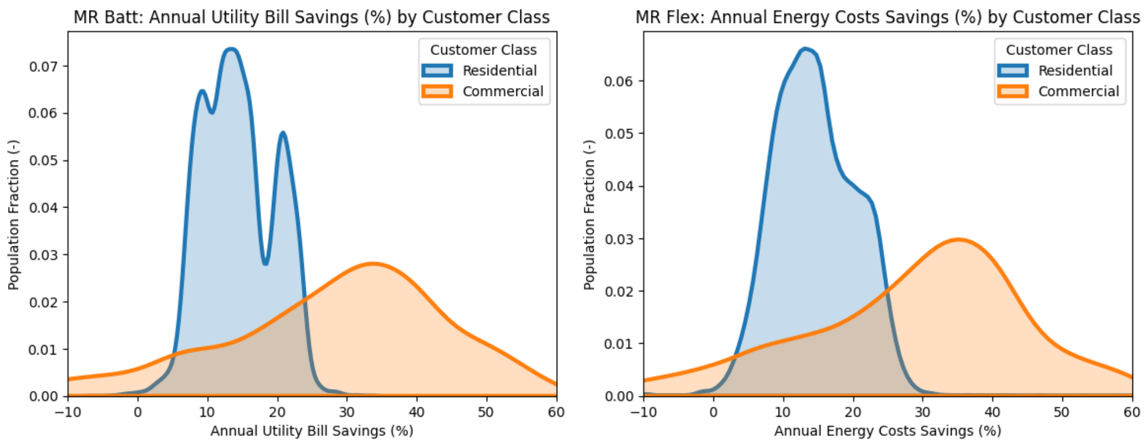


Figure 59. Comparison of annual energy expenses for participating residential and commercial customers for the MR battery (left) and MR flexible load cases (right).

4.2.2 Seasonal (Monthly) Variation of Bill Impacts

The previous section detailed the distribution of annual customer energy usage and resulting electricity costs. It is also important to understand the monthly distribution of these impacts, particularly electric utility bills, throughout the year. If participating in a transactive rate provided a customer average annual savings but resulted in higher bills a few months of the year (for example during peak summer cooling or winter heating) that could place financial burdens on customers and limit enrollment. This study analyzed the distribution of monthly electricity bills across the customer population. Figure 60 shows the monthly customer bill distribution and difference versus the BAU case for a summer peaking DSO (DSO #1) under the moderate renewable case. In this case, there are decreases in average customer bills throughout the year including in the peak summer months of July and August. A very small fraction of customers sees an increase in bills during the winter heating season (December and January). Similar trends are seen for the high renewables scenario (Figure 61) and for a winter peaking DSO (DSO #7: Figure 62 and Figure 63).

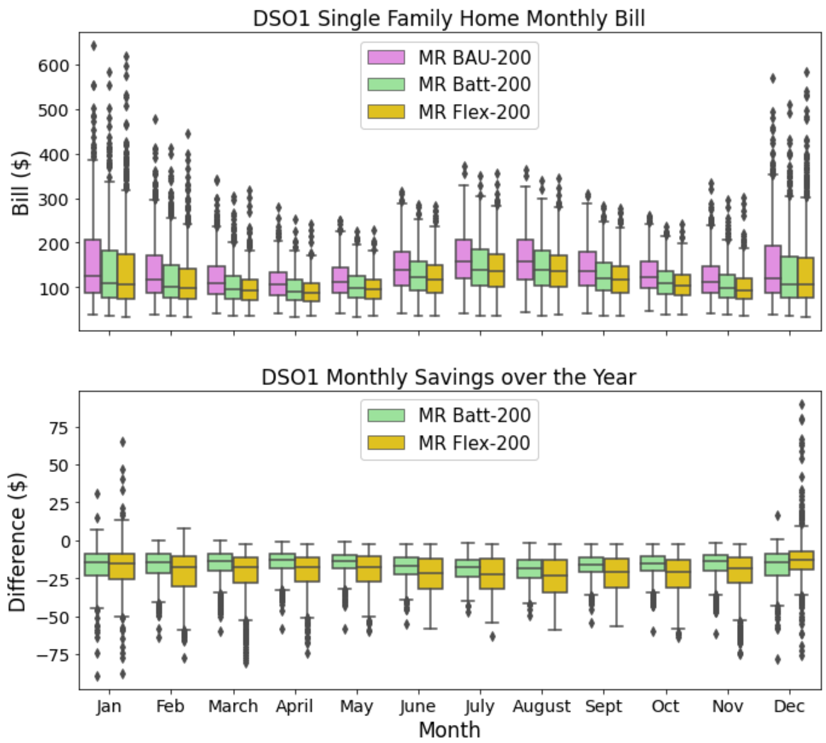


Figure 60. Distribution of monthly customer bills (top) and difference versus the BAU case (bottom) for a summer peaking DSO (#1) under the moderate renewable scenario.

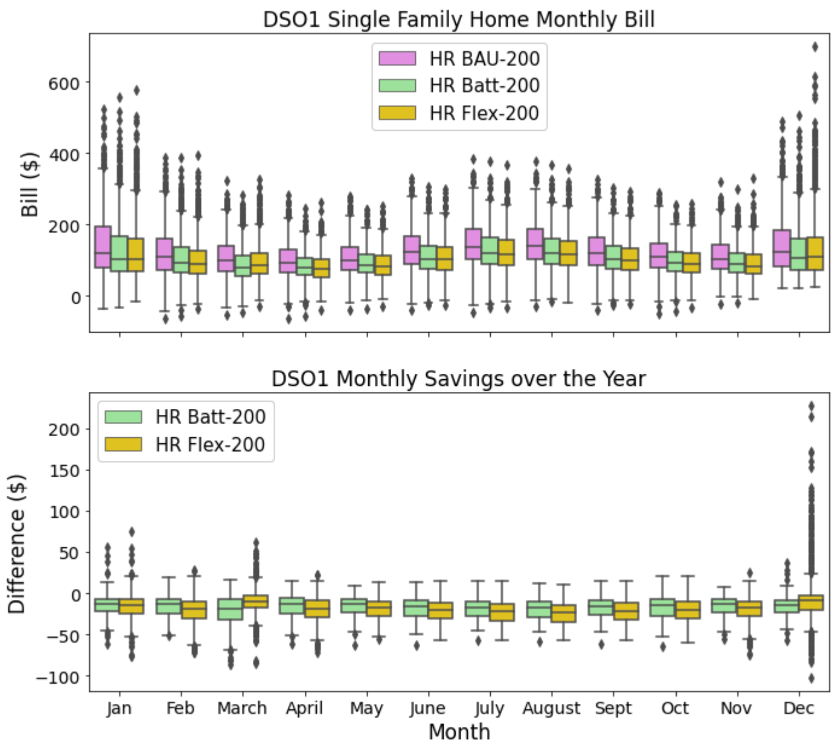


Figure 61. Distribution of monthly customer bills (top) and difference versus the BAU case (bottom) for a summer peaking DSO (#1) under the high renewable scenario.

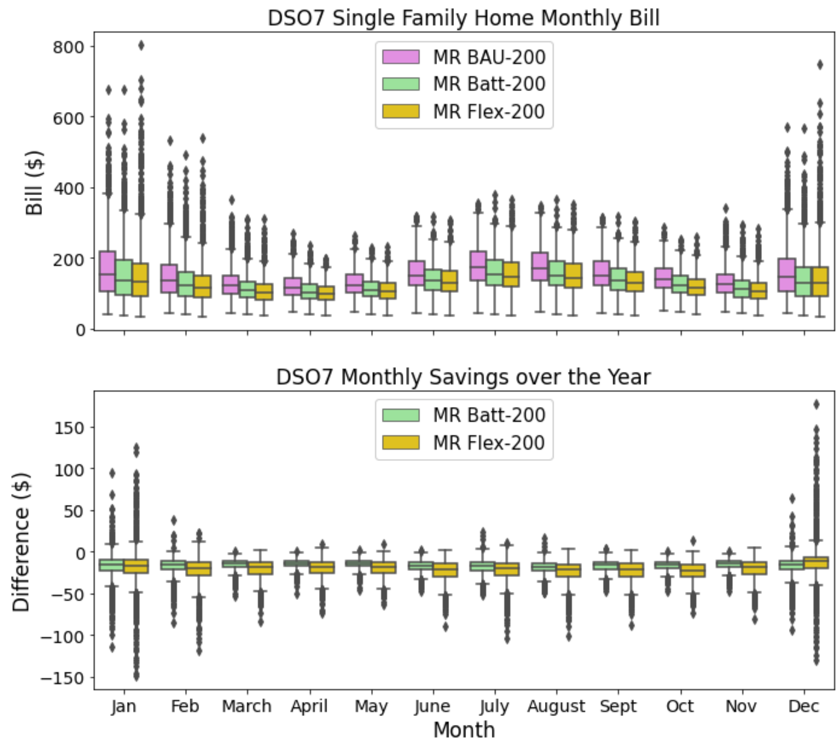


Figure 62. Distribution of monthly customer bills (top) and difference versus the BAU case (bottom) for a winter peaking DSO (#7) under the moderate renewable scenario.

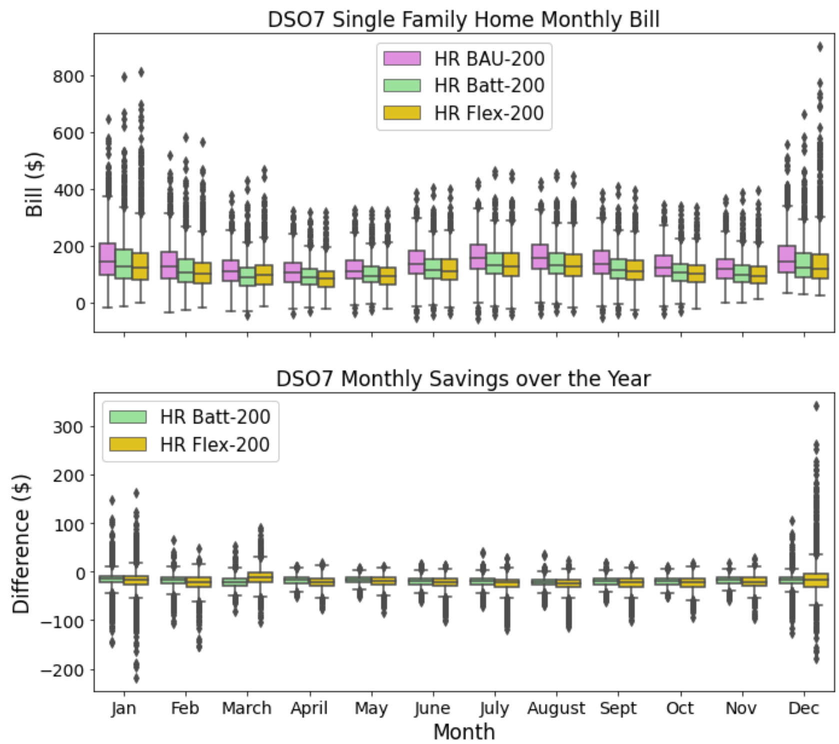


Figure 63. Distribution of monthly customer bills (top) and difference versus the BAU case (bottom) for a winter peaking DSO (#7) under the high renewable scenario.

4.2.3 Customer Savings by Participation Level

The impact of slider setting (sensitivity to price changes) on annual utility bill savings is shown in Figure 64 for a single DSO. The slider setting is configured by customers based on the level of flexibility they would like to offer. A slider setting of zero corresponds to a preference for increased comfort and amenity while a slider setting of one corresponds to a preference for increased savings. While there is a slight increase in savings as slider setting is increased, it is lower than expected. This is likely due to two reasons. First, the rate design provides meaningful savings (10%) to non-participants who provide no flexibility. This may attenuate the range of savings that participating customers may experience. More importantly, for HVAC control this study assumed that a slider setting of zero enables 2 F of thermostat setback and a slider setting of one equates to a maximum setback of 5 F. HVAC flexibility may experience diminishing returns at higher slider settings with most of the available flexibility being achieved with a setback of only 2 F.

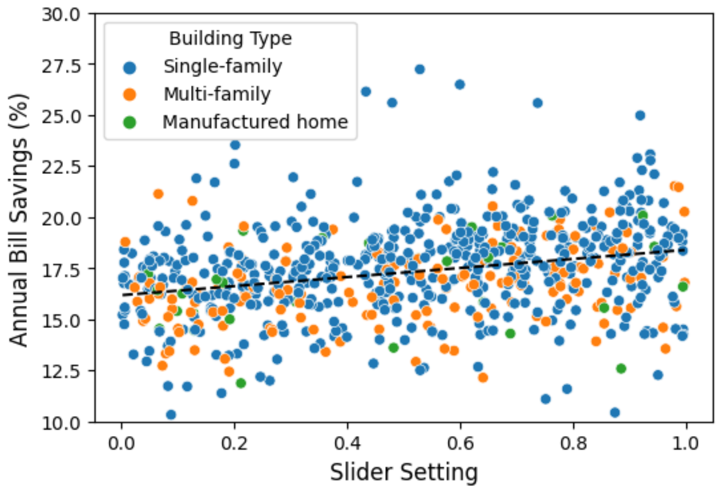


Figure 64. Annual bill savings as a function of participation level (slider setting) for residential customers (MR Flex case, DSO #1).

4.2.4 Customer Savings by DSO, Building, and DER Type

The granularity of the simulation allows customer benefits to be investigated as a function of DSO, building, and DER types. Since the majority of the system-level benefit is a function of the reduction in coincident load and wholesale energy purchases by each DSO only modest changes were seen as a function of these other factors. The impact of DSO type (rural, urban, and suburban) on residential customer energy expenses is shown in Figure 65. Greater savings are seen in the larger urban DSOs due, in part, to the DSO implementation costs not scaling linearly with number of customers (as will be discussed in 5.0). The urban distribution is also swayed by the one outlier DSO (#166) that experienced substantially higher wholesale energy expense savings and hence overall savings. If the distributions were weighted by regional customer population (not simulation population) its contribution would be substantially diminished. Suburban and rural DSOs show similar performance, with suburban DSOs showing slightly higher savings as their buildings are typically larger and some have higher reductions in wholesale energy purchases.

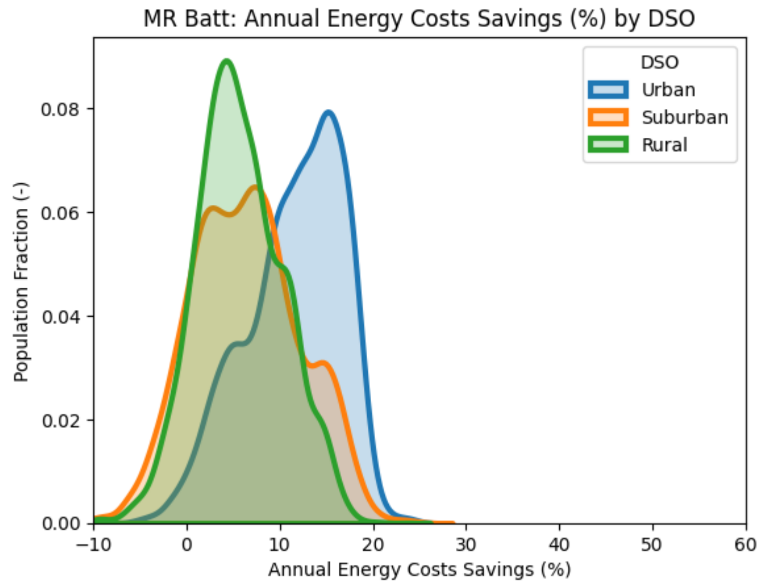


Figure 65. Residential customer annual energy expense savings as a function of DSO type (MR battery case).

The analysis shows similar relative savings between residential customers in single-family, multifamily, or manufactured homes (Figure 66, left). Similar relative benefit was seen as a function of heating type (Figure 66, right). While we do see variations in energy consumption as a function of building and heating type (as discussed in Section 4.1.1) the relative electric bill savings is similar due to a large portion of the transactive bill remaining as a volumetric charge.

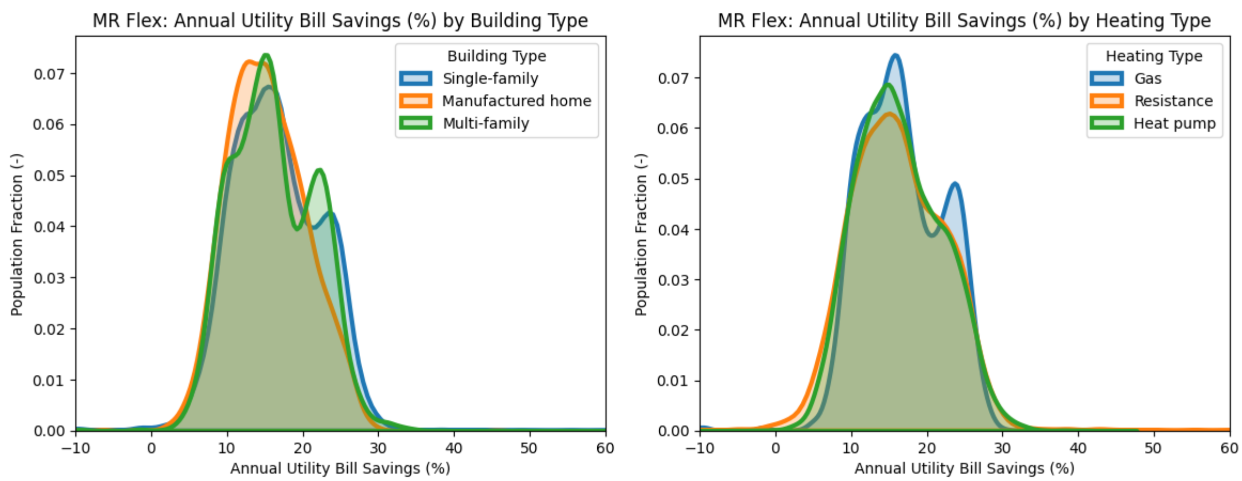


Figure 66. Residential participating customer bill savings as a function of building type (left) and heating type (right) for the MR flexible load case.

The high renewable scenario, which included the presence of EVs, allowed the performance of various combinations of flexible assets to be investigated. For the flexible load case there is similar performance for all the flexible asset combinations (Figure 67, right). This is due, in part, to HVAC, WH, and EV assets having lower implementation expenses (as compared to batteries) associated with the marginal cost of provisioning smart connected controllers. Also, the customer population in the flexible load case is dominated by HVAC participation, as 90% of customers have HVAC in this summer peaking region. Only a very small portion of customers had participating EVs and no HVAC system. There were no customers with stand-alone participating water heaters, so the performance of these systems could not be investigated in isolation.

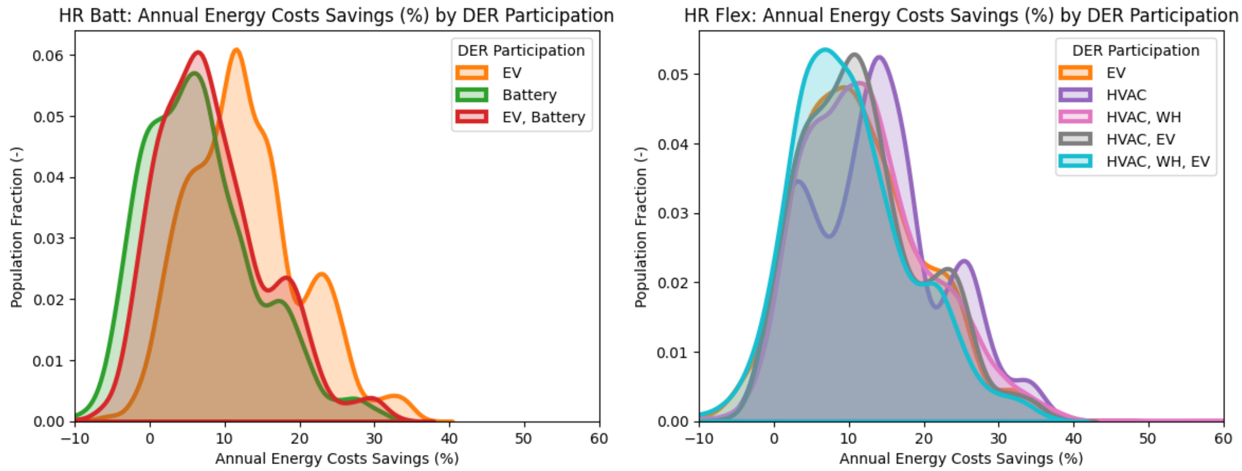


Figure 67. Annual energy expense savings of participating customers with different combinations of battery/EV (left) and flexible load/EV (right) flexible assets. HR scenario.

Unlike flexible loads and EVs, we assume that customers with batteries allocate the entire cost of ownership to their total annualized energy expenses (albeit, assuming aggressive reductions in battery cost). This results in customers with batteries alone experiencing lower (but still beneficial) average annual savings in total energy expenses (Figure 67, left). This reinforces the importance of low (marginal) implementation costs to reduce the barrier to entry and preserve annual utility bill savings once all energy expenses are accounted for.

Finally, the impact that dynamic rates have on customers with rooftop solar is investigated. Figure 68 shows the relative utility bill and total energy expense savings for participating residential customers[1]. Solar rooftop customers still see substantial utility bill savings on a dynamic transactive rate versus the BAU fixed rate. This is because a large portion of the dynamic transactive rate still comprises of a volumetric charge that recovers delivery and DSO operation expenses. The dynamic real-time portion of the transactive rate is designed to only recover wholesale energy purchase costs, which make up approximately 30% of total cost of grid operation. Customers with rooftop solar have slightly lower savings than those without rooftop solar. This is because these customers, who are still on net metering but with a time varying rate, now typically experience lower prices during the day when rooftop and utility-scale solar is in abundance, reducing the wholesale cost of electricity, and therefore reducing the avoided cost and overall benefit of self-generation versus the BAU case.

[1] Note that a small portion of simulated rooftop solar customers had utility bills that were negative or very close to zero over the course of the year. Near-zero annual utility bills can result in asymptotic values of relative percentage savings. For this reason, the percentage change in annual utility bills were clipped to ±100%.

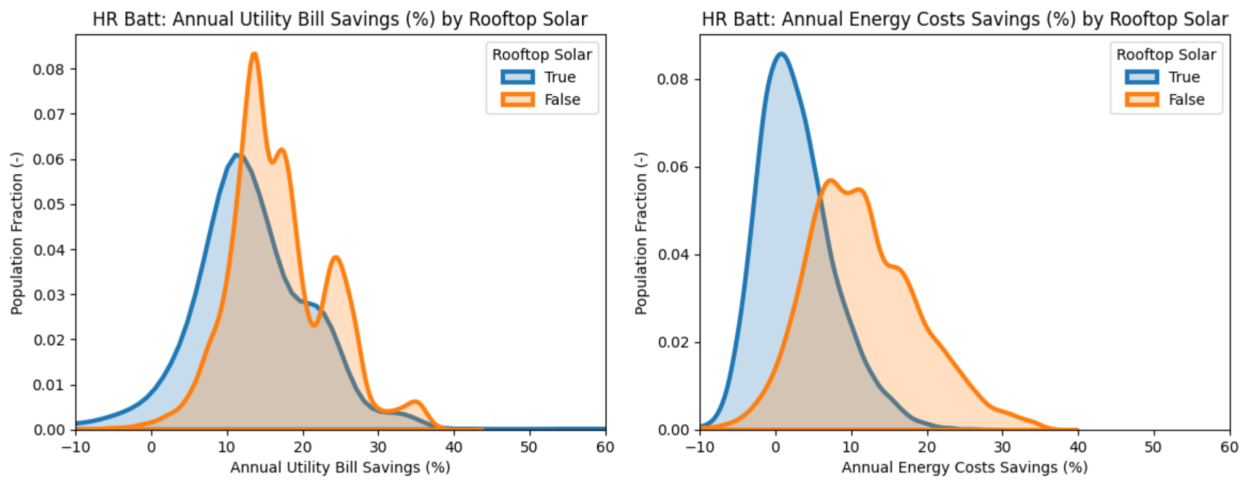


Figure 68. The difference in bill savings (left) and total energy expenses (right) for participating residential customers with and without rooftop solar. HR battery case.

The change in total annualized energy expenses for solar customers is shown on the right of Figure 68. They experience a larger decrease in savings when the expense of flexible assets (in this case batteries) is included. This is due to the simple reason that the average solar customer's annual utility bill is lower than a non-solar customer's bill. This results in the annualized expense of the flexible asset having a larger impact on the total annualized savings.

Table 18. Impact of EV and PV ownership on average energy metrics (and changes from the BAU case) of participating residential customers in the HR scenario.

Metric	All Residential	Without PV	With PV	Without EV	With EV
HR Battery Case					
Annual Energy (kW-hrs)	13000 (0.3%)	15840 (0.5%)	10610 (1%)	11360 (1.2%)	16980 (0.2%)
Peak Load (kW)	10.7 (-5.7%)	11.5 (1.1%)	12 (-4.9%)	9.7 (14.5%)	13.5 (-15.1%)
Annual Utility Bill ($)	1310 (-14.2%)	1520 (-16.8%)	1090 (-12.8%)	1130 (-15.5%)	1640 (-15.7%)
Annual Energy Expenses ($)	1880 (-8.2%)	1610 (-11.5%)	2890 (-2.8%)	1760 (-6.7%)	2220 (-10.9%)
HR Flexible Loads Case					
Annual Energy (kW-hrs)	12500 (-3.6%)	14300 (-3.1%)	8950 (-6.6%)	10680 (-4.9%)	16500 (-2.6%)
Peak Load (kW)	10.1 (-11%)	10 (-7.4%)	10.6 (-9.1%)	8.8 (-5.9%)	12.7 (-19.9%)
Annual Utility Bill ($)	1280 (-16.3%)	1430 (-17.2%)	990 (-14.3%)	1100 (-15.1%)	1660 (-14.8%)
Annual Energy Expenses ($)	1830 (-10.7%)	1460 (-15.2%)	2740 (-4.9%)	1650 (-11.5%)	2220 (-11%)

Key customer metrics by PV and EV ownership are shown in Table 18. These results reaffirm trends discussed above, namely that the customer population sees small increases in energy consumption in the battery case and small decreases in consumption in the flexible load case. In addition, EV owners provide the largest reduction in peak load due to their ability to implement managed charging. This is because the HR BAU case includes EVs without smart charging. Implementing price based smart charging reduces the peak loads of EV customers (by 15-19%). The battery case does have some customer populations that see (on average) increases in peak load. For example, customers who do not have PV (but may or may not have EVs) see a small increase (~1%) in peak load and customers without EVs see a ~15% increase in peak load. These are due to the impact of battery charging which, in these cases, cannot be offset by PV energy production or EV load shifting via smart charging. All customer groups see >10% reduction in their annual energy bills. Battery customers see lower total energy costs savings due to their larger investment costs and PV owners see lower relative savings due to their lower annual energy purchases and therefore lower absolute bill reductions relative to investment costs.

Finally, this analysis explored what percentage of customers paid more on their annual electrical bill (versus the BAU case) and by how much. Table 19 shows that PV owners had the highest proportion of customer who paid more under the transactive cases than the BAU case. Five percent of PV owners had higher bills for the battery case and 10% for the flexible load case. This small fraction of customers saw annual bills that were ~$50-60 per year higher (an approximately 5% annual increase). Only a small fraction of EV owners saw an increase (1-3%), but this customer class saw the largest absolute increase in annual utility bills of $110 per year (an increase of ~6%). Overall, only a small fraction (2-6%) of overall customers saw an increase in their annual utility bill. For customers who did see an increase, it was on average an increase of less than 5%. Further investigation is warranted to determine the magnitude of these trends in real customer populations and to better understand the attributes and behaviors of customers who might pay more under a given dynamic price rate design.

Table 19. Number (and percentage) of simulated customers who paid higher annual electricity bills (compared to the BAU case) by EV and PV ownership type and average annual bill increase.

Metric	All Residential	Without PV	With PV	Without EV	With EV
HR Battery Case					
Number (percentage) of customers	1233 (2.12%)	320 (0.78%)	913 (5.17%)	993 (2.43%)	240 (1.37%)
Average annual difference ($/yr)	$55.96	$78.79	$47.96	$43.82	$106.19
HR Flexible Loads Case					
Number of customers/Percentage of customers	3586 (6.13%)	1790 (4.39%)	1796 (10.17%)	3003 (7.34%)	583 (3.33%)
Average annual difference ($/yr)	$64.70	$68.43	$60.97	$55.72	$110.91

5.0 Distribution System Operator (DSO) Results

This section describes the DSO population and the resulting demographics captured in the study. It then provides insight into the economic performance of DSOs by type and the key factors differentiating cost savings.

5.1 Summary of Simulated DSO Population

If DSOs were modeled for all 200 nodes of the 200-bus model the vast majority of buses and associated DSOs would have few customers and small loads. For this reason, it was decided to simulate 40 DSOs. This results in approximately 90% of the system load being simulated but reduces the computational size of the model by a factor of five. The 160 buses that are not simulated were modeled using unresponsive load profiles. The selection of the 40 buses was not based solely on size. Selecting the largest 40 DSOs resulted in a selection that slightly overrepresented urban regions, investor-owned utilities, and summer peaking DSOs while underrepresenting cooperatives. Some adjustments in the DSO selections were made to counteract this. Six cooperative DSOs were added, five of which were rural. The resulting DSO selection still captured >89% of the system load, while reducing the computational size of the simulation by >80%.

Table 20, Table 21, and Table 22 show the resulting demographic mix and representativeness of the selections. Rural cooperatives are still underrepresented but less so than with a selection based solely on load. More importantly, this selection substantially increases the number of samples for both cooperatives and rural utilities, increasing the statistical significance of the study results for future analysis.

Table 20. Comparison of simulated DSOs by region type.

	Simulated DSOs	Target Load	Sim Load	Difference
Urban	9	65%	71%	-5.9%
Suburban	22	29%	26%	3.1%
Rural	9	6%	3%	2.7%

Table 21. Comparison of simulated DSOs by ownership type.

	Simulated DSOs	Target Load	Sim Load	Difference
Investor-owned	15	66%	71%	-4.1%
Cooperative	17	17%	11%	5.4%
Municipal	8	17%	18%	-1.3%

Table 22. Comparison of simulated DSOs by peaking season.

	Simulated DSOs	Target Load	Sim Load	Difference
Summer	27	89%	92%	-2.9%
Winter	9	6%	5%	1.0%
Dual	4	5%	3%	1.9%

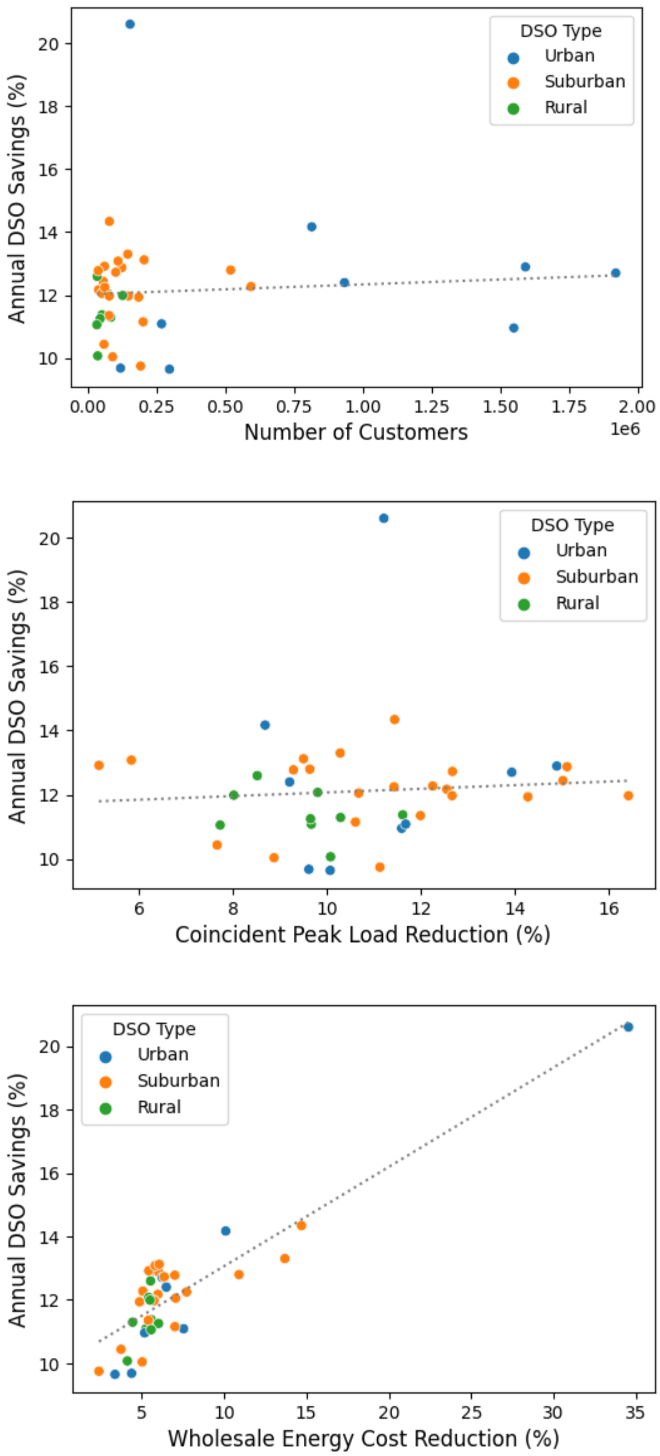


Figure 69. Net system benefit for each DSO as a function of number of customers (top), reduction in peak coincident load (middle), and wholesale energy savings (bottom) for the MR battery case.

5.2 DSO Savings by Type

The DSO attributes presented in the previous section allows the analysis of savings in terms of overall performance for all DSOs and as a function of DSO type (urban, rural, or suburban) and size. Figure 69 shows the reduction in expenses of each DSO as a function of size (number of customers), peak coincident load reduction, and wholesale energy savings for the MR battery case. There is small correlation between overall cost reduction and DSO size, with larger DSOs seeing slightly increased savings due to the implementation costs (particularly labor costs) not scaling linearly with DSO size. Furthermore, while the major driver of net benefit is the reduction in system coincident peak load, this is not the major factor differentiating the performance of various DSOs. This is because much of the reduction in capacity payment expenses comes from the reduction in capacity price, which is set by the reduction in system-wide coincident peak load, not reduction in a DSO-specific peak load reduction. Only the reduction in peak load capacity varies by DSO, resulting in a slight trend in increasing benefits with larger coincident load reductions.

The main factor that differentiates the individual savings of each DSO is its savings in wholesale energy purchases. This is a function of each DSO's demand flexibility, overall changes in annual energy consumption, and ultimately changes in its nodal LMPs throughout the year. For example, Figure 69 (bottom) shows an urban DSO (DSO #166) that has substantially higher net benefit savings than would be expected from its coincident peak load reduction. This increased benefit is due to demand flexibility providing substantial reductions in this DSO's wholesale energy purchase cost. DSO #166 experiences a 20% reduction in average day-ahead wholesale prices resulting in a 35% reduction in wholesale energy purchases (compared to a system-wide average reduction in energy purchases of 7%). This is likely due to demand flexibility reducing transmission congestion or enabling the dispatch of a lower cost generation reducing the LMP at this DSO's transmission node. DSO #166 is not large enough (with only ~1% of the total region's customers) to sway the overall trends. This result does show, however, the potential for demand flexibility to provide much larger benefits for individual DSOs with specific circumstances or constraints that are reflected in substantially different wholesale prices or large transmission and distribution investment cost deferral opportunities.

Figure 69 shows that urban and suburban DSOs have similar savings with rural DSOs having slightly lower savings. In addition, Table 24 shows similar levels of savings by DSO ownership type with cooperatives seeing slightly higher savings in the high renewable scenarios. Table 25 shows the savings by peaking season (summer versus winter) and shows slightly higher benefits for summer peaking DSOs in the high renewable scenario. Overall, the analysis shows that all DSOs saw meaningful economic benefit regardless of type, ownership model, size, or whether they are summer or winter peaking.

Table 23. Summary of DSO costs ($B) and percent savings by DSO type.

Type	MR BAU	MR Battery	MR Flex	HR BAU	HR Battery	HR Flex
Urban	19.9	17.4 (12.4%)	17.2 (13.4%)	18.9	15.5 (18.1%)	15.4 (18.6%)
Suburban	9.2	8.1 (12.2%)	7.9 (14.2%)	8.4	6.9 (17.6%)	6.7 (19.6%)
Rural	1.6	1.4 (11.4%)	1.4 (12.7%)	1.4	1.2 (13.2%)	1.2 (13.4%)
Total	30.7	26.9 (12.3%)	26.5 (13.6%)	28.7	23.6 (17.7%)	23.4 (18.6%)

Table 24. Summary of DSO costs ($B) and percent savings by DSO ownership model.

Type	MR BAU	MR Battery	MR Flex	HR BAU	HR Battery	HR Flex
Investor-owned	20.2	17.7 (12.3%)	17.5 (13.3%)	19.3	15.8 (17.9%)	15.7 (18.4%)
Cooperative	5.5	4.8 (12.3%)	4.7 (14.8%)	4.9	4 (19.5%)	3.8 (22%)
Municipal	5.0	4.4 (12.3%)	4.3 (13.6%)	4.5	3.9 (15.2%)	3.8 (16%)
Total	30.7	26.9 (12.3%)	26.5 (13.6%)	28.7	23.6 (17.7%)	23.4 (18.6%)

Table 25. Summary of DSO costs ($B) and percent savings by peaking season.

Type	MR BAU	MR Battery	MR Flex	HR BAU	HR Battery	HR Flex
Summer	27.2	23.9 (12.3%)	23.5 (13.6%)	25.6	21 (18.1%)	20.7 (19%)
Winter	2.3	2 (12.1%)	2 (13.3%)	2.1	1.8 (15.1%)	1.8 (15.5%)
Dual	1.2	1 (12.4%)	1 (13.7%)	1.0	0.9 (13.7%)	0.9 (14.2%)
Total	30.7	26.9 (12.3%)	26.5 (13.6%)	28.7	23.6 (17.7%)	23.4 (18.6%)

6.0 Discussion

6.1 Discussion of Study Results and Trends

This study has demonstrated that a transactive retail market is effective for a range of flexible assets, in cases of traditional flexible loads (such as water heaters and HVAC units) as well as stationary batteries, including the managed charging of EVs. The annual simulation of both cases across the moderate and high renewable scenarios provides insights into the relative suitability and potential of various flexible assets to manage load. Flexible loads provided effective response when grid constraints and price incentives are aligned with their operation. This is the case during the system's peak load that occurs during the summer afternoon, which aligns with peak HVAC operation and EV charging. EVs represent both a significant new load and a substantial new source of flexibility. Our modeling showed that if unmanaged EV charging is aligned with the system peak load, it would increase it 9%. Practically all this load could be shifted from the afternoon and evening peak to overnight hours.

Flexible loads were found to be less effective when grid needs did not align with the assets' availability or operation. For example, HVAC heating and EV charging provided only minor increases in minimum winter loads caused by the solar 'duck' curve. Batteries provided much greater flexibility and resulting reductions to daily system load variation during these times. This suggests the value of a mix of flexible assets: flexible loads that can alleviate their contributions to system peak loads and local delivery constraints; and batteries and other storage mechanisms that can address excess renewable generation that occurs at times that do not align with nominal loads, either due to mild temperatures not requiring space conditioning or EVs being in-use and away from charging stations. By design this study does not promote any specific mix of flexible assets or prescribe a renewable future scenario, but this could be the subject of future investigations.

As the electric grid decarbonizes, more of its operating cost will be associated with the recovery of capital infrastructure costs. This study shows (Section 2.1.5) that even today wholesale energy purchases represent less than a third of the grid's operating cost, with variable costs (fuel and variable generation O&M) accounting for less than 15%. Conversely, capital costs represent almost half (44%) of the grid's annualized cost while approximately 40% of the grid's cost structure is associated with labor, maintenance, and operations costs. Flexibility incentives and dynamic rate designs need to effectively address both energy market costs and infrastructure costs.

The designed transactive rate does effectively reduce capacity and investment costs, but more research is needed (and underway) into dedicated methods for dynamic capital cost recovery. Flexibility incentives also must not unfairly disadvantage any particular customer segment. An important feature of this study's rate design is the fact that nonparticipating customers share in the overall benefits. The customer rate structure assumes that nonparticipating customers remain on a fixed tariff and that this tariff is designed to recover revenue equivalent to the amount that would be collected if nonparticipating customers were on the dynamic transactive rate. This ensures that nonparticipating customers benefit from the reduced cost basis that the DSO experiences due to overall demand flexibility, thereby sharing in the savings. This ensures that customers who choose not to or are unable to install flexible assets (e.g., disadvantaged communities, renters, etc.) are not burdened by increased costs.

6.2 Discussion of Future Research and Capability Directions

The DSO+T study developed and exercised an integrated system and valuation model to assess the coordination of flexible assets at a scale and fidelity not achieved before. There are, however, several areas that warrant additional research and improved simulation capability. The representation of the business-as-usual system performance warrants investigation of customer load profiles to reduce the overprediction of the daily variation in system load. This potentially includes better representation of latent loads, industrial load profiles, building thermal mass, and the stochastic profiles of plug and miscellaneous loads.

Better representation of the spatial and temporal variation of wholesale system locational marginal prices, particularly infrequent but large increases in prices as well as the greater occurrence of negative prices is important to understanding the operation and value proposition of price-based DER coordination schemes. This includes improved representations of renewable generation curtailment schemes as well as the prediction of very low and negative wholesale prices during periods of significant renewable energy generation. Ensuring the price sensitivities of DSO demand bids are properly represented in the wholesale day-ahead and real-time markets will be important to investigating potential impacts to market price volatility and attenuation. In addition, it will be important to refine the representation of the generation capacity market and its associated rules given its prominence in the overall value proposition.

It is also important to understand the impact of improved DER coordination schemes on overall greenhouse gas emissions. This warrants the incorporation of generation emissions estimations and an associated emissions signal that could also be used to support DER coordination strategies. Hybrid value signals that incorporate price and emissions signals (such as an externalities tax) could incentivize shifting demand to periods of lower greenhouse gas emissions as well as lower marginal cost generation. Such an investigation can provide further insights into the impacts of engaging flexibility resources such as electric vehicles or transitions from gas to electric forms of heating.

Finally, it is important to continue to refine our understanding of the impact that DER coordination schemes will have on the economic outcomes of key stakeholders. Quantifying the economic impact on the generation fleet was outside the scope of this study. It will be important to understand the impact that demand flexibility (which flattens load and moderates wholesale prices) will have on required system capacity, generation revenue sufficiency, and ultimately resource adequacy.

This study did show economic benefits across a range of DSO types and sizes. We expect the actual benefits for a particular DSO to be a strong function of the regional capacity market (if present), wholesale energy prices (including the impact of transmission congestion), and the growth rates and capacity of their distribution systems. Investigating these benefits for a range of real distribution systems across the country would continue to advance our understanding of the value proposition. This would also identify the attributes of distribution systems that would experience the highest value propositions from DER coordination schemes and therefore the strongest financial incentives to adopt them.

Last, but most importantly, is the economic impact on utility customers. This study has shown benefits across a wide range of customer classes in a representative, albeit synthetic, simulated population. Confirming these benefits hold on real customer datasets and accounting for the covariance of DER ownership and incorporation of socio-economic metadata would provide additional confidence ahead of widespread deployment. There are also open questions on how to apportion the benefits between participating and nonparticipating customers. For example, should non-participating customers, who are not exposed to investment and price risks, pay a premium for retail price stability? Likewise, should participating customers, who invest money and time to participate and achieve the system level benefits, be incentivized to make these investments? These questions will need to be addressed in program and rate design.

7.0 Conclusions

The DSO+T study has successfully simulated a representative integrated electricity delivery system and associated economic cost model. This capability allowed the evaluation of the engineering and economic performance of a transactive energy coordination scheme. A distribution-level retail transactive energy marketplace was designed to integrate flexible loads, EV charging, and battery DERs into existing competitive wholesale markets including day-ahead and real-time market operations. Annual simulation results show that the transactive energy scheme provides effective and stable operation of a large penetration of DERs. Peak loads are reduced 9-15% and daily variation in load is reduced 20-44%. In addition, a rigorous economic assessment demonstrates that such an implementation would result in nominal savings to DSOs and customers of between $3.3-5.0B per year depending on future DER and renewable generation scenarios.

The majority of the economic benefit stems from the reduction in required capacity and associated reduction in capacity price. Sensitivity analysis demonstrates a positive value proposition even assuming low capacity-price reduction assumptions; however, given the capacity price's large contribution to benefits and the uncertainty about future load growth and generation capacity needs, this area warrants further investigation.

In addition, while wholesale energy purchases only contribute to approximately 25% of the cost to operate the grid, infrequent scarcity-driven events can cause large variations in wholesale price. Furthermore, the accelerated deployment of renewable generation will increase the period of time wholesale markets experience negative prices. Better understanding the value of demand flexibility during these market extremes will be needed given the increased likelihood of periods of generation scarcity and excess.

This study has also demonstrated that practically all DSO and customer types experience net benefits under a system with large amounts of demand flexibility. Investigating alternative dynamic rate designs and including customer socio-economic attributes will strengthen future investigations in this space.

The study's integrated co-simulation platform enables the detailed analysis and understanding of integrated bulk and distribution operation and coordination. Such a simulation platform will be required to also understand the operation of the grid (and resulting economic impact) in other possible future scenarios including much higher levels of renewables, incorporation of emission signals, alternative DER adoption mixes, and analysis of other regions and associated climates.

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