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Findings from an Advanced Demand Response Smart Grid Project to Improve Electricity Reliability in India

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***Abstract*—Two significant challenges for a reliable supply of electricity in India are increasing demand and generation deficits. Commercial and industrial buildings in India consume approximately 44% of the nation's electricity. India had a 4.7% supply deficit during the period of April to September 2014.[1] A smart grid initiative by Tata Power Delhi Distribution Limited (TPDDL) evaluated the technical capability and potential for increased reliability and readiness of commercial and industrial buildings for automated demand response (AutoDR). The advanced Smart Grid project included smart meters and an interoperable communication and DR management system with advanced data analytics for automated dispatch and load reduction when the grid is under stress. The project covered an area of more than 250 square kilometers and included about 167 high-end industrial and commercial customers in TPDDL territory. The study identified and characterized each consumer sector's load duration curve and aggregated power demand. A total of 144 consumers' 15-minute interval meter data was analyzed to identify the DR potential of each consumer sector using well-established baseline methodologies. The study characterized each customer sector's load profile and AutoDR measures and evaluated baseline models for the measurement and verification of customer's AutoDR performance. The study estimates the DR shed performance of AutoDR implementation for each type of consumer in the field study.**

Keywords— *Demand Response Potential; Automated Demand Response; Baseline Methodologies; Measurement & Verification; Load Duration Curve, Data Analytics*

I. Introduction And Background

India's peak demand deficit—the shortfall in electricity supply when demand is at the maximum—stood at 4.7% during the April to September 2014 period, according to data by the Central Electricity Authority (CEA) [1]. India's grid reliability has been improving with an increase in generation capacity and synchronization of the southern grid with the national grid. Even so, along with increasing power demand from the region, the peak power deficit is still an issue that needs to be resolved in the near future. The power deficit situation is worse in certain regions of the country (i.e., northern, southern). Solutions to address the deficit are either to increase the supply-side generation capacity or to reduce the electricity peak demand. With a focus on peak demand reduction, energy efficiency and demand response (DR) have been promoted as preferred resources. The Indian government has promoted energy efficiency through initiatives such as equipment levels, building codes, and others [2]. As a key demand-side management resource, demand response resources will provide the low-carbon flexible capacity needed to maintain real-time system balance and reliability with the integration of increasing levels of renewable energy resources [3].

A Smart Grid initiative by Tata Power Delhi Distribution Limited (TPDDL) was launched to conduct a field study of Automated Demand Response (AutoDR) with smart meters in New Delhi. AutoDR involves communication and control systems, where customer facilities respond automatically in receipt of an external grid signal. The goal was to evaluate the technical capability, potential for increased reliability, and readiness of commercial and industrial buildings for AutoDR. The advanced Smart Grid project included smart meters and an interoperable communication and DR management system with advanced data analytics for automated dispatch and load reduction when the grid is under stress. The project covered an area of more than 250 square kilometers with plans to enroll about 250 commercial and industrial customers in TPDDL territory. In this study, a total of 144 AutoDR customers' 15-minute meter data out of a total of 167 customers were analyzed for performance in 17 AutoDR events.

This study presents the measurement and verification (M&V) methods that are used to quantify AutoDR performance [4]. Each sector is grouped based on identified building types provided by TPDDL. Two types of baseline models were used to calculate the AutoDR performance during the event hours: (1) 5 out of 10 baseline days (used by TPDDL), and (2) 5 out of 10 baseline days with morning adjustment (research assessment) [5]. In summary, this study presents the statistical summary of the AutoDR performance for each customer sector and the aggregated load of the field study, in terms of kilowatts (kW) shed and percent kilowatts (%kW) shed over the whole building power (%WBP). The results of this study were deployed by two other companion

1 Central Electricity Authority (CEA), http://www.cea.nic.in/

studies that provided (1) characterization and effectiveness of DR technologies, and (2) scale-up of the field study to the Delhi region [6, 7].

TPDDL uses a 5/10-baseline with 24-hour data from smart meters to assess the customer performance of DR events. TPDDL selected this baseline after a thorough study of different baseline models that would be applicable (e.g., 10/10, 3/10, and 5/10 models with 8 hours and 24 hours of meter data) to the Indian conditions. The 5/10 with morning adjustment (MA) baseline for this study is evaluated as part of the research and extrapolated from the smart meter data. The analysis carried out using 5/10 MA baseline model requires further review with a similar set of customers. This analysis, which uses the smart meter data during AutoDR event days, is different from TPDDL baseline methodology that uses 5/10.

II. METHODOLOGY

The main objective of this study was to provide a statistically valid evaluation of the AutoDR performance of all participating customers in the field tests with TPDDL.

A. Consumer Characterization

A total of 167 customers included various types of load characteristics, so we grouped those customers according to types of categories (cold storage, commercial, education, flour mill, hospital, industrial, pumping, retail, and "others"). We report a high-level overview of those customers in terms of the number of customers in each sector category, peak demand power, and load duration curve.

Number of customers and peak demand of each sector category provide the market potential for DR and the value of the field study to be used for a large scale of the DR market. Demand response shed of each sector category can be quantified in the field study, and that helps allocate DR resources and reach out to new customers with high potential of DR shed. The load duration curve is one of the best ways to identify DR benefits because it shows the aggregate demand of all customers for all the hours in the year ranked in descending order.

The characterization of customer type can help utilities estimate the flexible load potentials that can be targeted to specific customers and to evaluate customers' value in different DR programs (e.g., day-of or day-ahead DR).

B. Measurement and Verification for Demand Response

Measurement and verification (M&V) of DR refers to the quantification of the DR performance in terms of the following metrics: total DR (kW), DR per building's square feet or meter (W/ft^2 or W/m^2), and the DR percentage of the whole building power (%WBP) [8, 9]. Demand response M&V includes the settlement of the load changes achieved by each customer and the program level. Different M&V methods are used for various purposes based on DR resource characteristics such as load variability, weather sensitivity, etc., for DR settlement. These baselines can also be used to estimate large-scale potential of DR and impact assessment of the DR program, and for operations and planning of DR [4]. Our primary focus is on the baseline used by the TPDDL. We review other baselines as a reference point for future activities.

We focus on the assessment of the AutoDR performance for each customer sector. Each customer had a smart meter to measure the energy use at 15-minute intervals. In our study, all AutoDR test events' baseline loads were calculated using two models: simple average over the highest 5 out of 10 recent good baseline days (5/10 baseline), with and without morning adjustment (MA) [5], which are described below.

- **5 out of 10 baseline model (5/10)**: The 5 days with the highest average load during the event period were selected from the previous 10 days of good data (excluding weekends, holidays, a DR event day, and any operation off day). The average of the load over these five days was calculated for each time interval.
- **5 out of 10 baseline model with MA (5/10 MA)**: The morning adjustment is a ratio of (a) the average load of the first three of four hours before the event to (b) the average load of the same hours from the selected five baseline days. The adjustment factor is limited to ±20% of the customer baseline.

The 5/10 MA baseline is included in our research study as a reference, as it is shown to reduce the bias and improve the accuracy of DR estimates for facilities that have variable load and where energy use is sensitive to weather changes. This reference allows us to better characterize AutoDR performance for any future studies. This study did not analyze additional baseline models such as weather-regression models, which could also be considered for future initiatives.

The AutoDR performance represents the difference between the building's actual power on an event day and two baseline models. Weather sensitivity and load variability are two important metrics of building characteristics. Weather sensitivity is a measure of degree to which building loads are driven directly by local weather. As we know, building heating, ventilation and air-conditioning (HVAC) loads are affected significantly by the outside weather condition (e.g., outside air temperature, humidity, solar radiation). For building loads with high weather sensitivity, the average baseline model may underestimate or overestimate the DR shed if the AutoDR event day is much warmer or colder than previous baseline days. Load variability is a measure of how different the load profiles are from one day to another. In our analysis, we used 5/10 MA baseline as a proxy to understand the AutoDR performance impacts for weather changes and load variability.

III. RESULTS FROM DATA ANALYTICS

A. Customers' Charactertics

Data from 144 meters were received from all the participants in the field study. Table 1 shows the number of customers and the peak demand of each sector category. The industrial, flour mill, and commercial sectors comprise the largest percentage of customers—about 77%—excluding the "others" sector, which includes unidentified customer types. These three sectors also have the highest peak demand, which accounts for nearly 87% of the aggregated peak demand (over 25 megawatts [MW]). In the industrial consumer sector there are ten sub-level sectors that include manufacturers of food, glass, packaging, plastic, printing, shoes, and other goods.

TABLE I. NUMBER OF CUSTOMERS AND PEAK DEMAND OF EACH SECTOR CATEGORY

Customer Sector Category	Number of Customers	Meter Data Received	Peak Demand (kW)
Cold Storage	6	6	1,131
Commercial	12	11	4,646
Education	7	3	1,936
Flour Mills	27	25	7,265
Hospital	2	2	1,434
Industrial	94	77	10,044
Others	17	14	1,889
Pumping	4	3	556
Retail	4	3	62
All	173	144	25,259 (Coincident)

Of the aggregated demand presented in Figure 1, the 95th and 99th percentile of the demand are 21,477 MW and 23,322 MW, respectively. It means that reducing load during the top 70 hours would eliminate the need for 7.7%, or 1,937 kW, of the system demand for those customers.

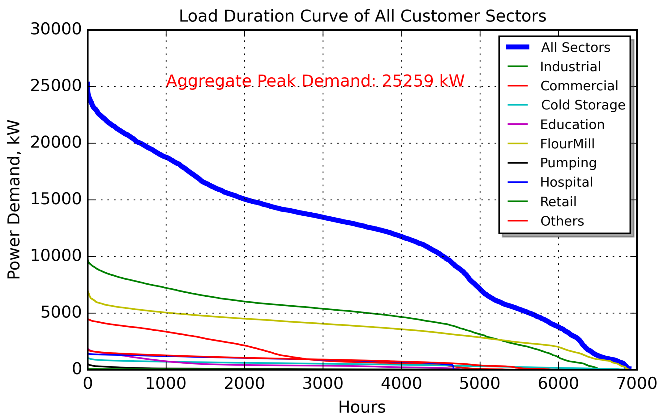


Fig. 1. Load Duration Curve of Each Customer Sector and Aggreated Load

B. Automated Demand Response Performance

We evaluated the effect of AutoDR in terms of those metrics: DR shed in terms of kW and %WBP (whole building power of the baseline).

- **kW shed**: The load shed potential of each customer sector, directly link to power supply and demand.
- **%WBP**: The percent of load shed over the whole building power baseline, which is used to identify each customer sector's end-use and relevant DR measures and quantify the aggregated load shed potential when scaling up the AutoDR implementation.

The metric to evaluate the AutoDR performance against the building size, W/ft^2 or W/m^2, was not reviewed, as we did not know the size of the building. As presented in Table II, a total of 17 test events were dispatched through TPDDL control center during the summer of 2014. More than 75% of the total test events lasted for an hour during the period of 3 PM~4 PM. The time scale covers most of high-demand hours from 12 PM to 6 PM, which helps us understand the DR shed potential of different times of high demand.

TABLE II. AUTODR TEST DATES, TIME, AND DURATION

Month	Day	Time	Duration (hr)
5	1	18:00~18:30	0.5
5	20	15:00~15:45	0.75
5	21	12:15~12:45	0.5
5	26	12:00~12:45	0.75
6	6	15:00~16:00	1.0
6	12	15:00~16:00	1.0
6	20	15:00~16:00	1.0
6	24	16:00~16:30	0.5
7	8	15:00~16:00	1.0
7	11	15:00~16:00	1.0
7	17	15:00~16:00	1.0
8	22	15:00~16:00	1.0
8	26	15:00~16:00	1.0
8	29	15:00~16:00	1.0
9	23	15:00~16:00	1.0
9	24	15:00~16:00	1.0
10	8	15:00~16:00	1.0

1) *Aggregated AutoDR Performance*

Figure 2 shows the aggregated AutoDR performance of two baseline models for all the 17 event days. The performance was not consistent for all the events. This study did not identify what contributed to the inconsistent performance. On June 6, 2014, performance was much higher than on other days. The load profile on this day is likely an anomaly, as there was a large load drop during the period from 12 PM to 7 PM, and requires further investigation. It is likely that missing meter data during the test period might be the reason. For the 5/10 baseline, which is used by TPDDL, the total reduction from all 144 customers for the best performing event was 8.6 MW; the second-best performing event was 3.2 MW; and the 75th percentile was 2.3 MW. Our analysis considers the 75th percentile, as it represents a conservative estimate of DR potential. The 75th percentile AutoDR performance was similar in both baselines: 5/10 and 5/10 MA.

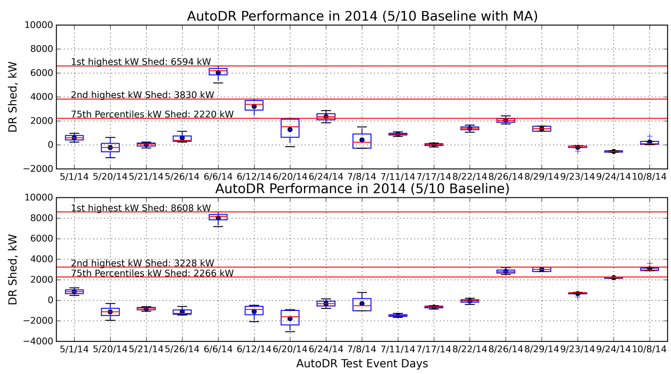


Fig. 2. Aggregated Load's AutoDR Performance on All the Event Days in 2014

Figure 3 shows the AutoDR performance of all customers on two AutoDR event days in 2014. The AutoDR event occurred from 3 PM to 4 PM on both days.

The analysis shows that the 5/10 MA baseline is better in closely matching the customer's load profile. This analysis identifies instances where the 5/10-baseline either under-, or over-estimates the AutoDR performance. For example, for the August 22, 2014 event, the 5/10-baseline underestimates the shed by about 1,450 kW. For August 26, 2014 event, the 5/10-baseline overestimates the shed by about 760 kW. The findings from AutoDR performance against the two baselines indicates that, in future, it is important to review different baseline models to improve the accuracy customer's DR estimates.

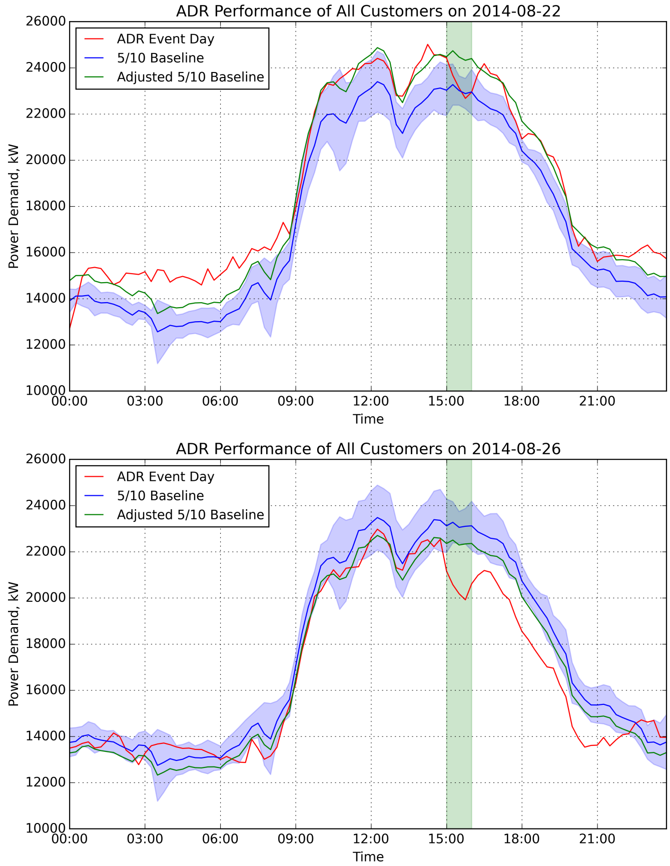


Fig. 3. AutoDR Performance of All Customers of Two AutoDR Events in 2014

Table III presents the AutoDR performance summary of these two events using 5/10 and 5/10 MA baselines. The results show that: (1) on August 22, 2014, the average kW shed accounts for -0.3% and 5.6% of each baseline's peak demand during the event hour; and (2) on August 26, 2014, the average kW shed accounts for 12.2% and 9.2% of each baseline's peak demand during the event hour.

TABLE III. AUTODR PERFORMANCE ON TWO EVENT DAYS

August 22, 2014			
DR Shed Metrics		**5/10 baseline**	**5/10 baseline with MA**
kW	Max	206	1,647
	Avg	-74	1,377
%WBP	Max	0.9%	6.7%
	Avg	-0.3%	5.6%
August 26, 2014			
DR Shed Metrics		**5/10 baseline**	**5/10 baseline with MA**
kW	Max	3,185	2,421
	Avg	2,817	2,053
%WBP	Max	13.8%	10.8%
	Avg	12.2%	9.2%

2) AutoDR Peformance for Customer Sectors

Figure 4 shows each customer sector's performance for all 17 DR events in 2014. It is clear that the AutoDR performance of each customer sector is not consistent through all 17 test events. Of those customer sectors, pumping, retail, and cold storage are the top three highest %kW shed over each sector's peak demand on the AutoDR event days. Pumping sector is a good resource in a regular DR program or an ancillary service DR program. Because the pumping operation schedule can be adjusted or allocated, this type of customer has significant DR potential; it can turn off all the pumping equipment for a short period. Similarly, due to the large amount of product mass stored in cold storage, this type of customer also has a large DR potential; it can shut down the storage equipment for a short period without affecting food quality [10]. Among those sectors, the flour mill, industrial, and commercial sectors provide the largest DR shed potential, which is 1,637 kW, 972 kW, and 360 kW, respectively, at the 75th percentiles of all AutoDR events. It should be pointed out that the aggregated DR shed is not equal to the sum of each sector's kW shed. The aggregated demand is calculated as the aggregation of data from all 144-customer meters. Because each customer's AutoDR performance and participation trend was not consistent through the 17 events, the aggregated kW shed is much less than the sum of each sector's DR shed potential.

As mentioned in the section on consumer characterization, information on each sector's DR shed potential can help a utility design the DR program, allocate the DR resource, and reach out to new market participants. Each type of consumer sector has specific DR characteristics in terms of time scale and DR shed potential.

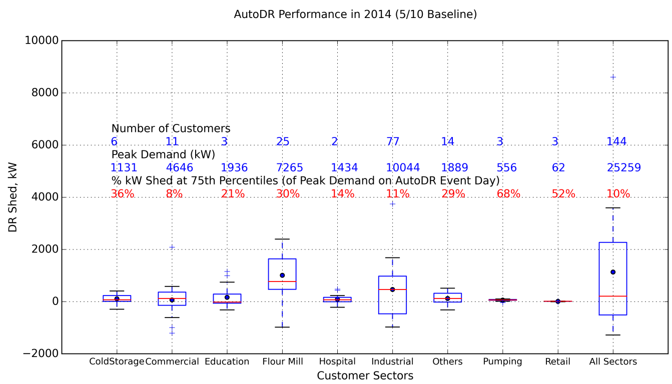


Fig. 4. AutoDR Performance of Each Customer Sector of All AutoDR Events in 2014

Table IV and Table V present the statistical summary of each customer sector's statistical AutoDR performance of all test events over the two baselines (5/10 and 5/10 MA). The kW shed and %WBP at the 75th percentiles match closely in both baseline models, while the mean aggregated AutoDR performance over the 5/10 MA baseline is about 460 kW higher than that of the 5/10 baseline, which is 40% of the mean aggregated kW shed. The 75th percentiles of kW shed, which can be a good representation of DR potential of each customer sector and the aggregated load, are 2,222 kW and 2,266 kW, respectively, for the 5/10 baseline with and without MA. For some customer sectors, such as commercial, education, and flour mill, there are large performance discrepancies between these baselines.

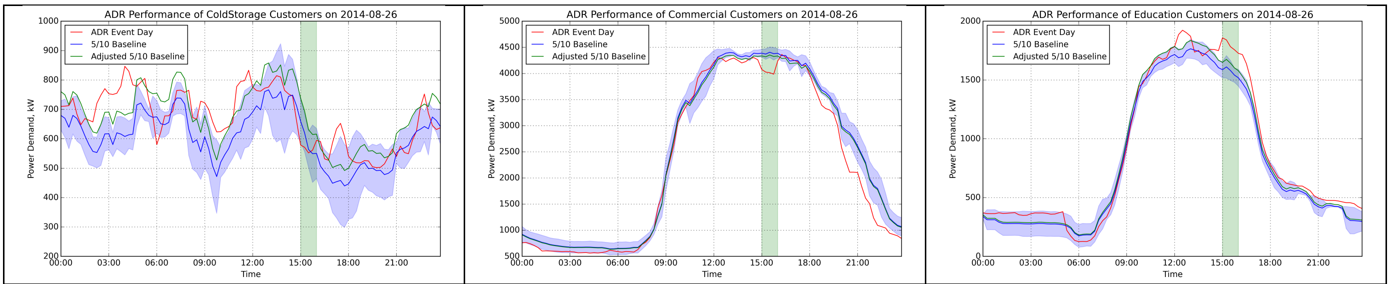
TABLE IV. AUTODR PERFORMANCE SUMMARY OF EACH CUSTOMER SECTOR (BASED ON 5/10 BASELINE)

Sector		**Cold Storage**	**Commercial**	**Education**	**Flour Mill**	**Hospital**	**Industrial**	**Others**	**Pumping**	**Retail**	**Aggregated**
kW	**Max**	403	2,086	1,154	2,397	482	3,741	512	103	28	**8,608**
	75th	229	360	289	1,637	160	972	318	80	12	**2,266**
	Mean	106	60	163	1,007	89	463	116	54	9	**1,133**
%WBP	**Max**	76%	59%	99%	62%	36%	50%	45%	84%	79%	**48%**
	75th	36%	8%	21%	30%	14%	11%	29%	68%	52%	**10%**
	Mean	19%	-2%	12%	20%	6%	6%	10%	44%	27%	**6%**

TABLE V. AUTODR PERFORMANCE SUMMARY OF EACH CUSTOMER SECTOR (BASED ON 5/10 BASELINE WITH MORNING ADJUSTMENT)

Sector		**Cold Storage**	**Commercial**	**Education**	**Flour Mill**	**Hospital**	**Industrial**	**Others**	**Pumping**	**Retail**	**Aggregated**
kW	**Max**	314	962	940	2,430	481	2,469	566	249	31	**6,594**
	75th	170	348	41	1,141	226	956	364	86	16	**2,222**
	Mean	110	316	28	778	131	612	199	64	12	**1,591**
%WBP	**Max**	54%	40%	94%	62%	36%	40%	46%	84%	78%	**42%**
	75th	34%	8%	3%	19%	18%	10%	26%	62%	50%	**10%**
	Mean	22%	9%	2%	16%	10%	8%	16%	45%	35%	**8%**

Figure 5 shows the AutoDR performance of each customer sector on August 26, 2014. The blue line in the graph shows the average 5 out 10 baseline days' load profiles, and the shading area indicates customers' load variability in terms of one standard deviation. In general, most customer sectors have a clear DR shed performance during the event hour from 3 PM to 4 PM, especially for industrial, flour mill, and commercial sectors. On this event day, the flour mill sector has a large load variability of the selected five baseline days. This results in the overestimation of shed that is almost twice that of the adjusted baseline. The use of facility equipment on the AutoDR event day may be much different from that of use on previous baseline days, as each customer in the flour mill sector has a different equipment operational schedule. MA baseline can be used to account for this change, to adjust the baseline for a better quantification of kW shed.



Cold Storage | Commercial | Education

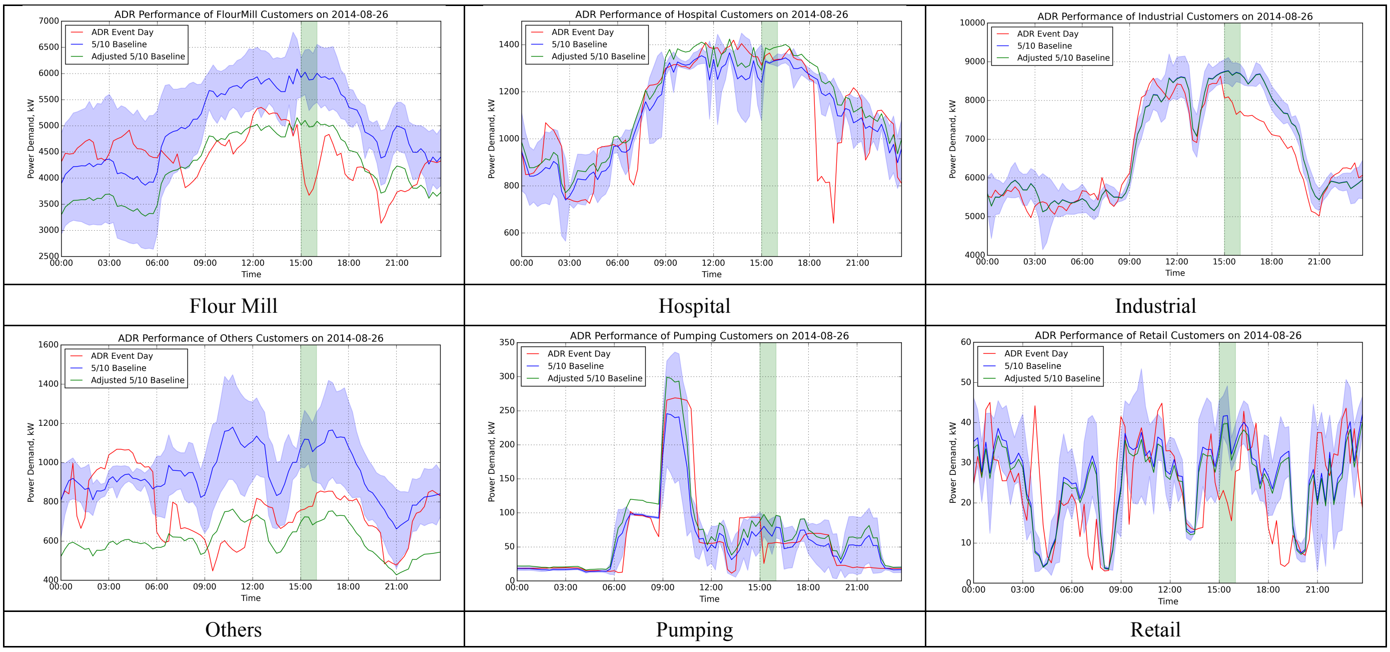


Fig. 5. AutoDR Performance of Each Customer Sector on August 26, 2014

IV. Conclusions and Future Work

In this paper, we introduced the Automated Demand Response (AutoDR) project launched by TPDDL and discussed the performance of all participating customers on 17 test event days. Smart meter data for 144 AutoDR customers were collected in this study and contributed towards an aggregated shed potential of nearly 10% of the peak demand (25,259 kW) against a 5/10 baseline. We grouped all the 144 customers into different sectors with similar functions, load profiles, and load shed characteristics. A data analytical framework was developed to calculate statistical analyses of AutoDR performance, based on the 5/10-baseline model, which is used by TPDDL. The 5/10 MA baseline model was also analyzed to study the impact of load variability in customer's AutoDR performance.

A. Conclusions

This study provided conclusions in the two key areas: (1) characterization of the customer sectors or groupings, and (2) DR performance assessment using measurement and verification methods for DR shed quantification. These results should aid utilities and regulators to identify improvements in the scaling of DR programs and market design.

1) Customer Groupings

A total of 9 groups of customer sectors were grouped based on each type of customers' specific load characteristics, which include cold storage, commercial, education, flour mill, hospital, industrial, pumping, retail, and "others." For the industrial sector, a group of 12 sub-level sectors are characterized; these include food processing, plastic, shoes, packaging industrial, etc. Of those groups of customers, industrial, flour mill and commercial sectors contribute the highest peak demand (~22 MW), which accounts for nearly 87% of the aggregated peak demand (~25 MW). In the future, each customer sector's load characteristics and DR shed potential will provide the value for scaling up this project that offers an additional DR shed potential to the market [7].

2) AutoDR Performance: Each Customer Sector and Aggregated

Key information about the AutoDR performance of each customer sector and aggregated load are presented here, focusing on the M&V method, statistical summary of the load shed, DR measures, and cost.

M&V Methods: The 5/10 baseline and 5/10 baseline with MA provide similar kW shed and %WBP AutoDR performances at the 75th percentile for all 17 AutoDR events. The use of 5/10 baseline models by TPDDL is a good start. For some customer sectors with high load variability, the 5/10 MA baseline can provide more accurate estimates of kW shed.

AutoDR Performance: (1) Overall the AutoDR performance of the field study was not consistent throughout the test events. We need to investigate if this is due to lack of financial incentives and credits for performance or customer/facility characteristics. (2) The flour mill, industrial, and commercial sectors contribute the largest of AutoDR load shed, which can shed up to 1,637 kW, 972 kW, and 360 kW, respectively, for 5/10 baseline (representing 19%, 10%, and 8% of each sector's peak demand on the AutoDR baseline day). The aggregated customer load can shed 10% of the aggregated peak demand at the 75th percentiles of all AutoDR performance for both 5/10 and 5/10 MA baselines.

DR Measures and Enablement Cost: TPDDL followed a common strategy for all the consumers; it involves the curtailment of non-critical load with consent of consumers. Non-critical loads were not clearly identified for this study; those loads are most likely weather-independent loads. Further investigation is required to identify the DR measures for each type of consumers and link them to the enablement cost for evaluating the cost effectiveness of DR in India's DR market.

More details can be found in our companion paper [6, 7]. Based on the methodologies of consumer characterization and M&V for demand response, the analysis results indicate that this field study is a successful implementation of AutoDR infrastructure and related technologies such as advanced metering infrastructure smart meters, wireless communication networks, and DR and meter data management systems. The aggregated load shed up to 10% of the aggregated coincident peak demand over the entire period from April to October in 2014. However, the AutoDR performance was not consistent on each event day, which indicates that there is much more DR shed potential to explore, to see if there will be financial incentives and credits for customers with good performance. Demand response measures implemented in the field study were very effective by switching ON/OFF the non-critical load. More importantly, extensive baseline model studies will be required to evaluate the quantities of DR shed when customer load profiles are more likely weather sensitive and unpredictable using the simple average baseline model.

B. *Future Work*

In addition to the MA baseline, future M&V frameworks must include consideration of the impact of weather changes, and develop a weather regression baseline model if the DR measures are related to building HVAC control strategies. While there is no one baseline that is a best fit for all customers, the best baseline specific to each customer sectors could be used to estimate DR potential for a larger customer group. This exercise is useful to for better defining the value of DR and various DR measures for different types of customers. Future work will also focus on better understanding of customer sectors and end uses for load-effectiveness and cost-effectiveness of AutoDR. These activities will develop the value of DR in India's electricity grid, and increase DR implementation and customer acceptance.

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BIOGRAPHY

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