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Demand Response Implementation for Improved System Efficiency in Remote Communities

Pilot Results from the Village of Hartley Bay

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***Abstract*— This paper evaluates the performance of a demand response (DR) system, installed in the remote community of Hartley Bay, British Columbia, which is used to reduce fuel consumption during periods of peak loads and poor fuel efficiency. The DR system, installed to shed load during these periods, is capable of shedding up to 15 per cent of maximum demand by adjusting wireless variable thermostats and load controllers on hot water heaters and ventilation systems in commercial buildings. The system was found to be successful in reducing demand by up to 35 kW during the DR event period, but caused a new, time-shifted "rebound" peak of 30 to 50 per cent following each event. A DR "staggering" method is introduced as a tool for reducing and delaying rebound without affecting occupant comfort and safety.**

In this work, load prediction models based on linear regression and averaging of historical data were also developed for measuring DR shed and rebound, with models based on averaging found to produce more accurate baselines.

Keywords - Smart Grids; Energy Conservation; Demand Response; Load Prediction; Implementation Challenges; Energy Management; Energy Control

I. Introduction

High costs, cost uncertainty and environmental issues associated with using diesel fuel for generation are a concern in isolated communities [1], where electricity prices are often many times that of large utility-connected systems due to lack of economy of scale [2]. Therefore, even small improvements in utilization of the community electric power system can have substantial economic benefits by reducing operating costs. One option for improving system efficiency and reliability, and the focus of this work, is to use a demand response (DR) system to prevent inefficient states of generator operation. A smart meter system can be used to verify the benefits and develop triggering points [3], [4] and an energy management information system (EMIS) can be used to plot and measure savings.

This paper highlights the details of a comprehensive demand response program in the Village of Hartley Bay, which was run to improve overall electrical generator dispatch efficiency by shedding loads during certain peak demand periods. It does this by adjusting wireless controlled variable thermostats and load controllers on hot water heaters and ventilation systems in commercial buildings.

The project was conducted in four phases. The first was defining the specific problem being addressed by the DR program (Section III in this report). The second was deciding how success of the program would be measured and how baseline demand would be forecasted (Section IV). The third phase was running the specified DR program and the final phase was analysis of the results and recommendations for future DR programs (Sections VI through VIII).

II. Background

There is a significant body of government and academic research surrounding DR, load prediction, and the relationship between these two topics.

A. *The Village of Hartley Bay*

The Village of Hartley Bay, located approximately 650 km North West of Vancouver, BC, is a remote coastal community in the Gitga'at Nation. The community is home to 170 residents living in 82 buildings: 62 residential and 20 commercial/mixed use. The village is isolated from the main electricity distribution network and relies exclusively on local diesel generators for electricity. Since 2008, Hartley Bay has been engaged in an energy management initiative aimed at reducing greenhouse gas (GHG) emissions. One focus of this initiative is managing all aspects of the electrical network including generation, distribution, and demand. Several energy management initiatives have been implemented including installation of a wireless network of smart meters, monitoring of energy use in real-time using an EMIS, lighting, heating and HVAC retrofits and hiring of local energy coordinators to manage projects and engage the community [5].

A DR system was proposed to shed community loads during peak periods in order to keep demand below 360 kW and therefore avoid dispatching of the 210 kW generator. In the spring of 2010, a DR system consisting of twenty variable thermostats and twelve 30-amp load controllers was installed in several commercial buildings in the community. An audit of the facilities determined that the loads with the highest energy usage and the lowest chance of occupant disturbance were baseboard heaters, hot water heaters, and HVAC systems. In order to further minimize the chance of occupant disturbance, a manual DR override was also installed. The total demand under DR control is 61.3 kW, or approximately 15 per cent of the average maximum community demand. The current DR setup in Hartley Bay allows for both manual and automatic decision-making. Under the manual configuration, a human decision-maker must observe and predict periods of peak load and manually trigger a DR event using the web interface. The automated configuration allows for a regular DR event to be run at a certain time of the day and/or certain days of the week [5].

B. Consequences of Demand Response

One well-documented consequence of DR is the “rebound effect,” sometimes referred to as the “payback effect.” This term describes the tendency of electrical loads to produce a demand spike while “catching-up” to normal operation immediately after a DR event ends. The magnitude of this effect differs depending on the building and equipment involved in the DR program. One field study of residential water-heater control in Norway showed an average shed of 0.5 kW during DR events, but a rebound in the hour following the event of up to 0.28 kW, or 56 per cent of the average demand shed [6]. A 2007 Lawrence Berkeley National Laboratory (LBNL) paper suggests that the rebound effect can be mitigated by bringing the electrical system back to normal operating conditions slowly rather than immediately after an event (a strategy called “rebound avoidance”) [7]. This rebound avoidance strategy is incorporated into the load controllers in Hartley Bay, which return to normal operation randomly over a 15-minute period once the DR event is complete. The thermostats do not have this built-in rebound avoidance.

Another possible consequence of DR is a reduction in occupant comfort within the facilities under control. For example, a 2011 study of automated control of air conditioning and lighting in a Tokyo office building led to reductions of between 10 per cent and 23 per cent of peak demand, but a reduction in occupant comfort led the authors to conclude that a “more acceptable control strategy” would need to be developed [8].

C. Electrical Load Prediction and Forecasting

Electrical load prediction refers to the output of a statistical model, regardless of whether the load being modeled occurs in the past, present or future, while forecasting specifically refers to the prediction of future loads [9]. Several complex statistical models have been developed for load prediction, including those that use artificial neural networks [10] [11], but this type of modeling is beyond the scope of this study. Rather, simpler models were examined.

One popular prediction method is linear regression of historical demand data with weather and time-of-week inputs. As LBNL points out, regression models are easy to interpret and modify, they are not computationally intensive, and they tend to compare well against other load prediction models [12]. Another prediction method seen in the literature uses averaging of historical load data [13].

A separate LBNL study multiplied the prediction data by an “adjustment factor,” defined as the “*ratio of the actual to the predicted load in the two hours prior to the event period,*” to correct for forecasting errors early in the data set being analyzed. They show that both weather regression and historical averaging-based models produce better results when this adjustment factor is applied [13].

III. Utility of Demand Response

Electricity in Hartley Bay is generated by three diesel generators, one 210 kW and two 420 kW. In October 2009, precision fuel flow sensors were installed on the three generators and generator efficiency, defined as litres of fuel consumed per kWh of electricity produced, was determined. The 420 kW generators were shown to have the highest efficiencies (0.27 L/kWh or 34 per cent) while the 210 kW generator had the lowest efficiency (0.49 L/kWh or an average of 19 per cent). It was concluded that, in order to maximize the efficiency of the generation system and minimize fuel consumption, the 210 kW generator should be run as little as possible [1].

As demand in the community increases or decreases, different generator combinations are dispatched to increase or decrease capacity, respectively. An increase in capacity is called a generator "pickup,” while a decrease in capacity is called a generator "dropout.” In 2010, the generator dispatch settings were optimized to reduce fuel consumption while maintaining system reliability. The new dispatch settings are shown in Table I. Under these settings, the 210 kW generator is run when the total community demand drops below 105 kW or increases beyond 360 kW. An analysis of historical energy consumption data shows that, on average, community demand exceeds 360 kW only 3687 minutes per year, or roughly 0.7 per cent of the time. Based on the generator fuel efficiencies measured in [1], avoiding all occurrences of this peak demand would save approximately 27,000 L of fuel per year, or 5.0 per cent of the annual fuel consumption.

TABLE I. Hartley Bay Generator Dispatch Settings [1]

Capacity Change	**Generator Combination (G1 = 210 kW, G2 = 420 kW)**	**Pickup/Dropout Power (kW)**
210 kW to 420 kW	G1 to G2	120
420 kW to 210 kW	G2 to G1	105
420 kW to 630 kW	G2 to G1 + G2	360
630 kW to 420 kW	G1 + G2 to G2	325

IV. Modeling Typical Demand

In order to quantify the results of the DR program, baselines were first developed to represent “what would have happened” had the DR events not been triggered. Several baselines were developed using various prediction models, and the most accurate baselines were then selected to quantify the experimental results. The prediction models used fall into two general categories:

1) *Averaging of historical demand profiles, and*
2) *Regression of historical demand with weather and time variables*

Six representative days were chosen where a demand response event was manually triggered for evaluation of the various forecasting methods. For each baseline, an “adjustment factor” similar to that used in [13] was applied. In this case, each baseline was adjusted by a factor equal to the ratio of the actual to the predicted load in the 1.75 hours prior to the DR event.

The data predicted by the chosen models were compared to the actual data set before and after the DR event (including rebound and settling period) to measure the accuracy of each baseline. In other words, a perfect baseline, as measured according to this methodology, would follow the actual data at all times except for between the DR and rebound period. The error in the model was quantified using root-mean-square (RMS) error and mean bias measurements.

TABLE II. Prediction Model Accuracy

DR Data Set	Best Baseline Prediction Model	RMS Error (kW)	RMS Error (%)	Mean Bias (kW)
Total Community, Average of all DR-Days	Average Non-DR Day	8.60	2.87	-2.5455
Total Community, Single DR-Day (Feb 24, 2012)	Median Non-DR Day	17.76	5.77	-1.1883
Total Community, Single DR-Day (Feb 15, 2012)	Dec-Jan 2012 Average (Adjusted)	25.78	7.82	0.8636
Health Centre, Average DR Day	Feb-Mar 2012 Average Non-DR Day (Adjusted)	2.27	11.09	0.2468
School, Average DR Day	Feb-Mar 2012 Average Non-DR Day (Adjusted)	0.69	10.56	-0.2449
Gymnasium, Average DR Day	Feb-Mar 2012 Average Non-DR Day	0.81	10.72	-0.1211

Table II shows the best baseline prediction model along with the RMS error and mean bias of the baseline for each of the six DR-day data sets. As shown in column 2 of the table, in all cases the prediction models based on average (or in one case median) historical data performed better than regression models. Furthermore, applying an adjustment factor improved the baseline in three of the six data sets analyzed. This result differs from that in [13], where a similar adjustment factor improved all baseline predictions.

Overall, producing accurate baselines for the Hartley Bay load data was a significant challenge as reflected in the relatively high RMS error values in Table II. The minute-level load data showed many high-frequency swings in demand (similar in appearance to signal noise) that the models were unable to predict, which contributed to the high error values. Averaging of load data to filter out these swings was considered, but this would have eliminated many short-lived peaks exceeding 360 kW and skewed the final results.

V. Experimental Design

In order to maximize the value of the DR system, 3 years of historical community-level demand data was analyzed to determine the time-of-day at which demand was most likely to exceed 360 kW. The results of this analysis are shown in Fig. 1. The chart represents the number of weekday occurrences of demand exceeding 360 kW, separated by the time-of-day at which they occurred. It is clear from the analysis that demand levels greater than 360 kW are most likely to occur between the hours of 8:00 to 9:15 and 15:00 to 20:00.

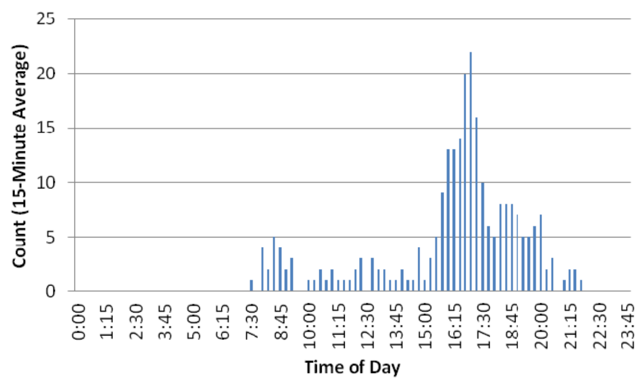

Fig. 1. Occurrences of Demand Exceeding 360 kW by Time of Day (Weekdays, 3 years of data, 15-minute averaging)

Once the system was commissioned and manually tested for several weeks, an automatic schedule was implemented to help avoid human error and ensure that DR events were run at the same time each DR-day. The schedule was originally set to run two, 30-minute load-shed events each day: one at 08:00 and one at 17:00. However, during initial commissioning and testing some occupants perceived a “cold” environment (due to the shedding of the thermostats) or a “stuffy” environment (due to suspension of the ventilation fan operation) when they first arrived in the morning. To avoid this, the schedule was altered to run only at 17:00, a time at which most commercial buildings in the community see less usage and have been heated by the daytime thermostat schedules.

In both cases, the schedule was run Monday, Wednesday, and Friday ("DR-days"), with the other days of the week left as control days (i.e. "normal' or "non DR-days"). A shed period of 30 minutes was chosen in order to minimize any effects on building occupants. Manual testing was performed throughout the month of January 2012, while the automatic schedule ran events on Monday, Wednesday and Friday for the entire months of February and March 2012. At the time the data was collected, building-level data from the Health Centre, School and Gymnasium was available up to March 16, 2012 and community-level data was available up to March 6, 2012.

Smart meters in the community collected real-time energy data and an EMIS was used to organize and export the data for the purposes of designing the program and verifying the results.

VI. RESULTS

Results of the DR program effectiveness were measured according to criteria developed by LBNL in [12]. They define a "DR residual," that is the DR event period plus a one-hour post-event "rebound period," and suggest several parameters for quantifying the residual. Four of the LBNL parameters were chosen to quantify the DR residuals in Hartley Bay. The parameters and results for each of the six data sets are shown in Table III. Detailed results are discussed below for two example cases: the average of all DR-days for a single building and a single DR-day for the entire community.

TABLE III. DR RESIDUAL MEASUREMENT RESULTS

DR Data Set	DR Residual Metric			
	Average Demand Shed (kW)	Average Rebound (kW)	Peak Demand Ratio, Actual/ Predicted (%)	Energy Consumption Ratio, Actual/ Predicted (%)
Total Community Average DR-Day	14.42	14.41	105	101
Total Community Single DR-Day (Feb 24, 2012)	35.87	16.59	112	100
Total Community Single DR-Day (Feb 15, 2012)	26.60	9.99	114	100
Health Centre Average DR Day	16.18	3.34	120	97
School Average DR Day	0.83	1.17	N/A[1]	105
Gymnasium Average DR Day	2.21	1.15	N/A[2]	101

[1,2] The peak demand for the School and Gymnasium occur long before and long after the DR event, respectively, so the peak demand ratio is not a useful DR metric in this case.

A. *Single Building Analysis – Gymnasium*

The Gymnasium average DR-day demand and baseline are plotted in Fig. 2. As discussed in the last section, DR events were run at 17:00 to coincide with total community peak demand (although the load in this particular building experiences a local minimum at 17:00). A total load of 13.68 kW is under DR control in the Gymnasium, 88 per cent of which is a large hot water tank. The average demand shed in the building is 2.21 kW, while the average rebound is 1.15 kW, or 52 per cent. The one-sigma confidence interval for the prediction values is ± 0.81 kW (approximately ± 11 per cent).

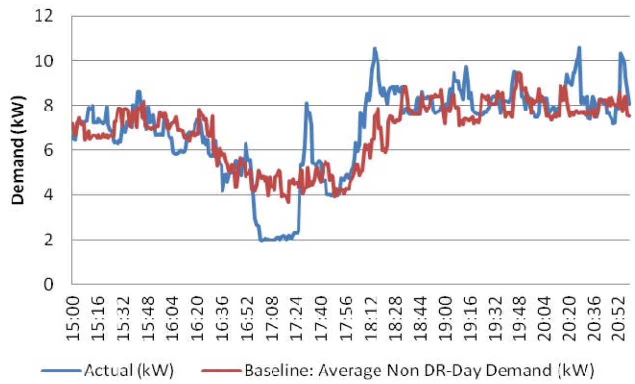

Fig. 2. Gymnasium Average DR-Day Demand with Baseline

The shape of the rebound is unusual for this facility. After the (expected) initial rebound spike, the load appears to produce additional spikes approximately every 30 minutes until the end of the data period. These periodic rebound spikes may be due to the hot water tank heaters, which use basic "on-off" type control, oscillating until the tank temperature is re-stabilized. The rebound spikes produced several new peaks, each one greater than the peak that would have occurred had the DR event not been triggered (i.e. the peak predicted by the baseline).

B. *Total Community – Single DR-Day*

Community-wide demand data for a single DR-day in February along with the best baseline are shown in Fig. 3. Average demand shed is 35.87 kW and average rebound is 16.59 kW, or 46 per cent. The one-sigma confidence interval for the prediction values is ± 17.76 kW (approximately ± 6 per cent).

On this particular day, the baseline did not predict a demand peak exceeding 360 kW. However, the actual data shows a large, consistent shed, implying that the DR system would be successful in avoiding a 360 kW-plus peak if it were run at the appropriate time. However, due to the rebound effect, an even greater peak would be generated in the hour following the event. It is clear from this data that the rebound effect must be addressed in order for the DR system to be successful in avoiding generator step-up.

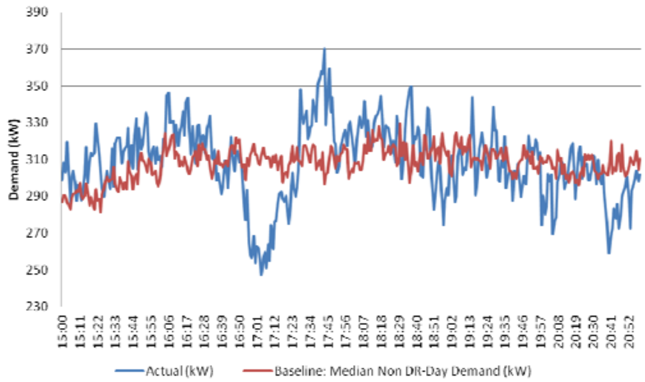

Fig. 3. Single DR-Day (Fri, Feb 24) Community-Wide Demand with Baseline

VII. REBOUND

Minimizing rebound can be accomplished in two main ways: reducing the magnitude of the rebound or delaying the rebound effect until the overall load is low and therefore the peak resulting from the rebound does not exceed the daily maximum demand value.

The collected data reveals that the magnitude of the rebound depends on at least two variables: the magnitude of the average DR shed and the type of equipment under DR control. It is therefore important to consider the rebound characteristics of different equipment types when assessing a building for DR. Also, because rebound is proportional to the DR shed (30 per cent to 50 per cent of DR shed in the data analyzed), there is a tradeoff between the amount of load that is shed and the resulting rebound peak. When designing any DR system, effort should be made to minimize the magnitude of the DR shed while still meeting the goals of the system (e.g. avoiding a certain level of demand). This could be accomplished by, for example, triggering only a subset of the total DR-controlled buildings at any one time. Delaying the rebound can also be accomplished several ways. The most obvious is to increase the length of each DR event, although event length should be measured against possible effects on occupant comfort and safety. Another technique that could be used is "staggering" DR events among different buildings. If the events are timed correctly each DR shed could “cancel out” the rebound from the event before it.

A. *Simulation – Staggering Method*

To demonstrate this “event staggering” concept, a sample community consisting of four buildings under DR control was modeled. Actual load data from the Hartley Bay Health Centre was used for each building. That is, for the purposes of the model, all four buildings were assumed be identical to the Health Centre. As a control scenario, a 30-minute simultaneous DR event was first modeled in all four buildings (see purple line, Fig. 5). Because the buildings are modeled after the Health Centre, we know from the peak demand ratio in Table III that the resulting rebound generates a new peak 20 per cent greater than that in the baseline.

A second scenario was then modeled, where the DR events in each of the four buildings were staggered by 30 minutes. Fig. 4 shows each building load separately, while the green line in Fig. 5 shows the summed total demand of the four buildings (i.e. representing the total community load). As expected, the net DR shed is lower than in the control scenario because each shed event is reduced by the rebound of the preceding event. The net rebound, however, is delayed by 1.5 hours when compared to the control scenario and the magnitude is reduced to the point that it no longer creates a new maximum peak. Also, because the DR event time remains at 30 minutes for each individual building, it is unlikely that the staggered events would affect occupant comfort any more than in the control scenario. This staggering method has clear potential for reducing the rebound effect and therefore maximizing the benefit of DR programs.

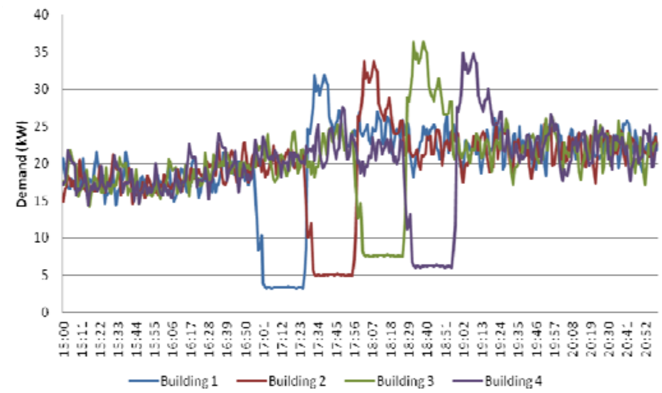

Fig. 4. Sample Community Load with Staggering (Individual Building Loads Shown Separately)

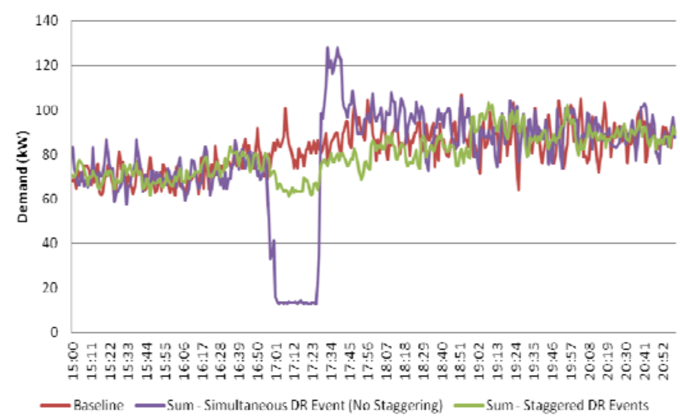

Fig. 5. Sample Community Load with Staggering (All Buildings Summed)

VIII. CONCLUSIONS

This project demonstrated that DR systems can be implemented in commercial/institutional facilities in a remote community and that the system can be remotely triggered in a reliable way. Furthermore, the project demonstrated the utility of minute-level power metering combined with an EMIS in both assessing opportunities for DR and evaluating the results.

Finding an accurate load prediction model for the highly variable Hartley Bay demand data was a challenging task and even the best models had a high degree of uncertainty.

Prediction models based on linear regression of historical data with outside temperature performed poorly versus models based on historical averaging. This is likely because the heating system in each building responds to changes in outside temperature with different time constants, while basic linear regression assumes an immediate response time. Furthermore, non-weather factors such as occupancy, community events, and building and equipment schedules likely play a significant role in shaping energy use. Detailed information on these non-weather energy drivers should be incorporated into future models.

Judging by the data sets analyzed, it is unlikely that DR events run throughout February and March of 2012 were successful in avoiding the generator step-up at the 360 kW community-wide demand mark. This is largely due to the rebound effect, which created a post-DR event demand peak that exceeded the baseline peak in every data set analyzed. This holds true even after the uncertainty of the prediction models is taken into account. For this reason, minimizing the effect of the rebound from DR on peak demand is of critical concern when implementing a DR program. This could potentially be achieved using the staggering technique modeled in this paper, which both reduces and delays post-DR event rebound without affecting occupant comfort and safety.

In the community of Hartley Bay, unlocking the full potential of future DR programs could produce annual fuel savings of up to 27,000 L, or 5.0 per cent of the total fuel consumption.

IX. ACKNOWLEDGMENT

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XI. BIOGRAPHIES

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