Comparison Between Two MPC Algorithms for Demand Charge Reduction in a Real-World Microgrid System
UCR Sustainable Integrated Grid Initiative (SIGI)

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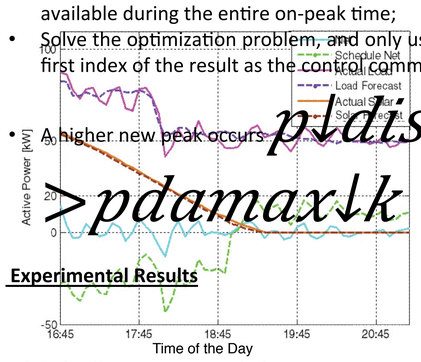
Abstract

This paper describes an evaluation between two model predictive control (MPC) algorithms for microgrid energy management combined with solar production and battery energy storage for demand charge reduction in a real-world microgrid system. The first control algorithm is a constant threshold MPC (CT-MPC) that works well on a system with relatively stable solar generation and a well-known building load profile. CT-MPC can maintain the on-peak demand under a certain value during the entire on-peak rate period. The second control algorithm is an adjusting demand threshold MPC (ADT-MPC). ADT-MPC can better deal with unpredictable solar generation and/or changing building loads. The on-peak threshold under this algorithm is adjusted to the optimal value during the on-peak rate period. As expected, The CT-MPC algorithm performs well when coupled with accurate forecast models, while the ADT-MPC algorithm excels when forecasting is more unpredictable.

CT-MPC Algorithm and Experimental Results

1. **Principles**
   - Charge the BESS when there's extra solar generation;
   - Calculate maximum average discharge power $pdavmax_k$ and $pdamax_k$ to make sure that enough remaining battery capacity is available during the entire on-peak time;
   - Solve the optimization problem, and only use the first index of the result as the control command;
   - A higher new peak occurs: $p_{kdis} > pdamax_k$



2. **Experimental Results**

Fig.4. Solar Generation and Building Load Experiment.

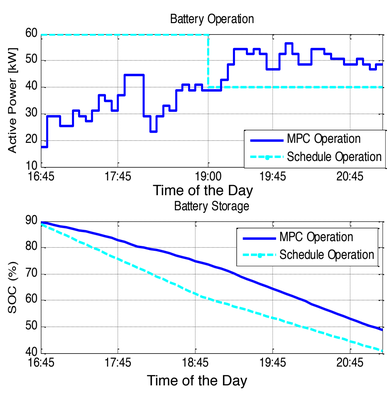


Fig.5. Battery Operation and SOC Level.

Fig 4 and 5 show a single-day experiment on 5/14/2015, under the winter season electrical rate schedule. In Fig.4, the *onPeakini* was set to 20 kW. It is clear to see that the net load was tightly controlled below *onPeakini*. 'Schedule Operation' in Fig.5 means the BESS was discharged at a fixed power for a certain period of time, without considering any system information.

Introduction to the Real-World System Model

❑ Battery Energy Storage System (BESS) Model

A 500 kWh Li-ion battery bank is installed in the SIGI testbed. To protect and prolong the lifetime of the Li-ion batteries in the microgrid, the SOC of the BESS is normally maintained between 40% and 90% . In cases where solar generation is low, and the building energy consumption is high, the SOC is allowed to go down to 20%, for these special cases. From the charging and discharging experiments, the battery operation can be modeled as a linear process:

$$\mathbf{bc}_L = \mathbf{bc}_{0L} - \gamma \cdot \mathbf{A}_L \times L \cdot$$

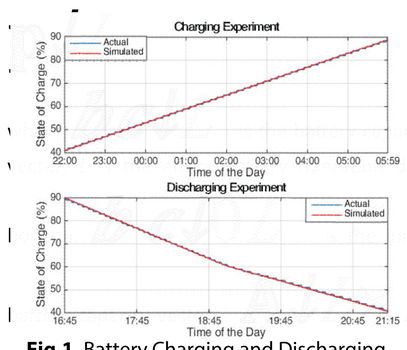


Fig.1. Battery Charging and Discharging Experiments.

is a lower triangular matrix; $\mathbf{p}_L$ is the battery operation vector; γ is the charging/discharging efficiency.

❑ Predictive Model

In the real system, both solar generation and building electricity usage should be predicted. For the given facility (1200 Building), the prediction model for solar generation and the building load profile are simplified by averaging the historical data and then updated at certain ratio comparing to the real-time solar generation and building load.

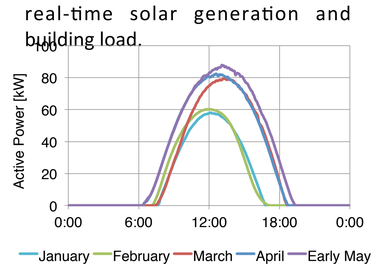


Fig.2. Average Solar Generation.

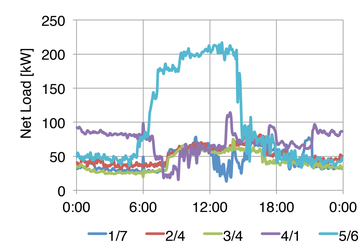


Fig.3. 1200 Building Load Profile.

❑ Optimization Model

The time-of-use (TOU) rate schedule includes two different cost components that should be considered in the optimization function. Therefore, the developed MPC control algorithms optimize for kWh and put a constraint to the kW demand to maintain it to the lowest value.

At each time slot k:

$$minimize\ (\mathbf{price}_L)_k \cdot (\mathbf{pex}_L)_k \cdot \Delta t$$

subject to:

$$(\mathbf{bc}_L)_k = (\mathbf{bc}_{0L})_k - \gamma \cdot \Delta t \cdot \mathbf{A} \cdot (\mathbf{p}_L)_k$$

$$0 \le (\mathbf{pg}_L)_k \le p_{max}$$

$$\mathbf{pex}_L(k) = (\mathbf{Pl}_L)_k - (\mathbf{Ps}_L)_k + (\mathbf{pd}_L)_k$$

$$0 \le (\mathbf{pex}_L)_k \le p_{max}$$

MPC Principles

MPC models have a prediction horizon M and a control horizon L. The detailed MPC principles can be applied as follows:

i. For each On-Peak rate period in a single day, the time intervals can be divided into M, where $M = hours \times 12 + 6$, $hours$ refers to the on-peak hours: in summer, $hours = 6$ (12:00–18:00) and in winter $hours = 4$ (17:00–21:00). The duration for each interval is 5 minutes. As electricity demand charges are calculated based on a 15 minutes moving average by the utility company, the battery bank is programmed to start discharging 15 minutes prior to the on-peak rate period start time, and stop discharging 15 minutes past the end time.

ii. Set control horizon L and prediction horizon M, and fetch the prediction model for solar generation and building load, $\mathbf{Ps}$ and $\mathbf{Pl}$ respectively. Additionally, fetch the electricity price $\mathbf{price}$ and set $disRate = 0.4$.

ADT-MPC Algorithm and Simulation Results

1. **Principles**
   - Use the first step of MPC optimization as the current control operation;
   - Use the second step of MPC optimization as the tracking parameter: tracking the SOC deviation (ΔSOC) between the actual change and the predicted change;

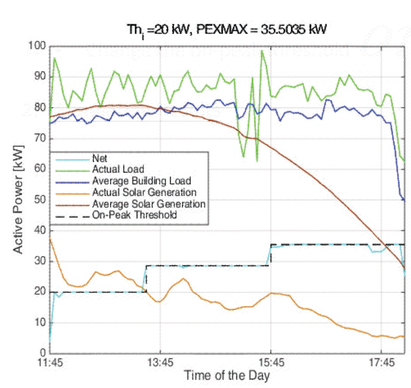


Fig.6. ADT-MPC Net Load Simulation Under a Cloudy Day on 6/9/2015.

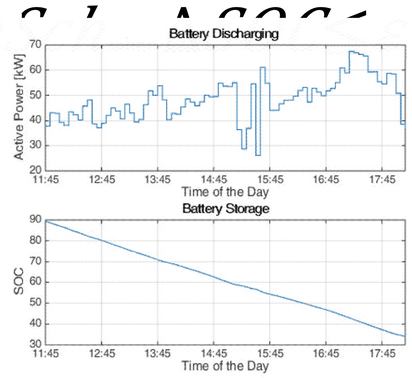


Fig.7. ADT-MPC Battery Operation and Storage Simulation Under a Cloudy Day on 6/9/2015.

Figs 6 and 7 are generated under cloudy weather conditions. The actual solar generation during this day is very low, which is much lower than the average solar generation profile. The actual building load profile of this day behaves randomly (increasing and decreasing throughout), which is at a high level compared to the average load profile. In Fig.6, the on-peak threshold increases sequentially two times, from 20 kW to 35.5 kW at 14:05 ($i=28$) and 15:45 ($i=48$). In Fig.7, the battery is discharged to 34.44% SOC which is still within the safety 20% SOC. Without the battery storage system, the maximum net load would have reached an on-peak demand value of 82.44 kW. With the help of the BESS contribution, the maximum net load is reduced by 43.12 kW.

Comparison Between ADT-MPC and CT-MPC

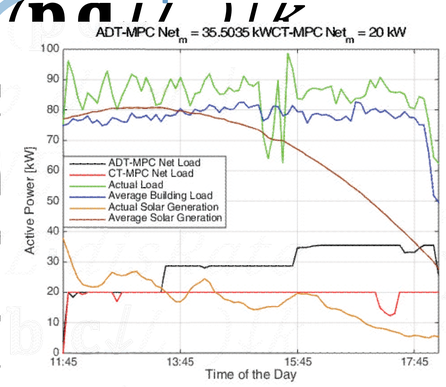


Fig.8. Net Load Comparison on a Cloudy Day.

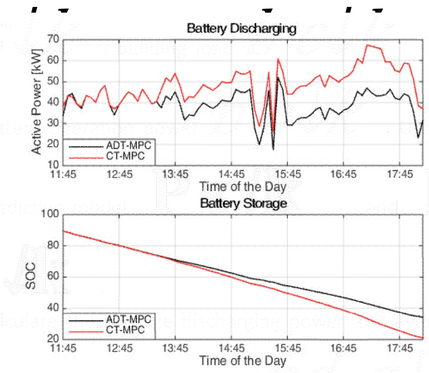


Fig.9. Battery Operation and Storage Comparison on a Cloudy Day.

Fig.8 shows the net load comparison between CT-MPC control algorithm and ADT-MPC control algorithm. The initial threshold is 20 kW. In this figure, it can be observed that the net load threshold has been adjusted to 39.32 kW under ADT-MPC operation while it is kept below 20 kW under CT-MPC operation. Initially, the first two hours of the battery operations are similar due to the similar demand threshold. After a couple of hours of operation, the threshold in the ADT-MPC algorithm is adjusted to a higher level due to the low solar generation. In Fig.9, the remaining SOC eventually decreases to 34% for ADT-MPC algorithm while it drops to the lowest level 20% in CT-MPC algorithm.

Conclusion

From Fig.8 and 9, it can be observed that CT-MPC will use the entire battery capacity to the lowest allowed SOC level (20%) to maintain the constant demand threshold, while the ADT-MPC algorithm adjusts the threshold to a higher value to maintain the battery capacity resulting in a higher SOC. The CT-MPC method was demonstrated to provide the lowest load demand resulting in lower battery SOC. The ADT-MPC algorithm maintains a higher SOC reserve capacity and is shown to be more responsive to demanding rate schedules and energy fluctuations. The CT-MPC performs well when coupled with accurate forecast models while the ADT-MPC algorithm excels when forecasting is more unpredictable. The ADT-MPC algorithm has the advantage of applicability to a highly variable system, when comprehensive historical energy generation or building load profiles are lacking.

Acknowledgements

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UC Solar South Coast AQMD Winston Battery