Distributed Rate Control for Smart Solar Arrays and Battery

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1 Introduction

As technology getting more advanced, solar electricity generation fashion has a large improved than before. In order to smartly utilize the production from solar panel and simultaneously balance the flow in power grid network, a scheduling algorithm applied to IoT devices can play a role of manipulating generation rate. In *Distributed Rate Control for Smart Solar Arrays*, they presented an algorithm attempts to control the rate of generation in order not to produce more surplus that might be injected into power grid. On top of that, they considered different weather situation as a factor as well. In the paper, although they are not focusing on battery equipment, they mentioned that battery in this system would be a complement. Therefore, this system could come up with a new aspect of problem or could be applied with other implementation to improve this system network.

2 Motivation

Tesla Powerwall
Tesla presented a power system including four units: powerwall, grid, solar, and home. Powerwall is a home battery that could charge by solar power and discharge when needed. This system is able to monitor electricity flow ongoing in user's home, and manipulate the portion of power from grid, solar, and powerwall. Although it's not clear whether how they deal with the problem for surplus producing, this overall system structure is a good model to base on.

Weather Forecasting
Weather forecast is always an important technique for human to foresee how the weather might be in the next few days. Accordingly, human would able to do some preparation or scheduling beforehand. Not only the precision is getting higher, but also data has become more reachable. Nowadays, as the technique of machine learning become more popular, more and more machine learning predictions have involved in weather forecasting. Moreover, solar power highly depends on the weather. That is to say, the prediction of weather can highly benefits solar generation if we can do some scheduling work beforehand.

User Habits
As the improvement of machine learning technique keeps going, plenty of companies have taken advantages from learning user habits. As the fact that, human tend to follow their own pattern when facing similar situation. For example, everyday route, daily electricity consumption, or even electricity product usage. Therefore, learning user habits make a system more easier to adjust themselves in order to be fitting in their life.

Electricity Rate
As you can imagine, human unevenly consume electricity in their daily life. People tend to have higher electricity demand in day time than how much they need during night. From the aspect of electricity retailer, a balanced consumption would be the best distribution instead. Therefore, the electricity unit price varies from day to night. Unit price during daytime would be higher. On the other hand, unit price at night is way lower.

3 Definition

Inspired by the Tesla powerwall system, it is feasible to applied the algorithm presented in *Distributed Rate Control for Smart Solar Arrays* and adding more advanced machine learning technique to make better use of electricity. For every home, the most dramatic reason to install solar panel and powerwall is probably the potential of reducing utility cost for them. Benefiting from the different utility prices, it is possibly to manipulate some of these points to end up with lower total cost on utility: **(1)How to maximize the usage of solar with the physical constraint of grid**, **(2)How to control the battery between discharge and charge mode**, **(3)How can we smartly exploit the period during lower unit price**

4 Approaches

Weather Prediction with Machine Learning
Solar array highly relies on the situation of weather. If it's a sunny day, generation would be way larger than the demand from the home. On the other hand, on a overcast day, total generation would not be able to sufficiently supply the whole family. However, in the paper, the solar array only able to manipulate generation rate based on current weather situation. Based on that, here I'm going to build this model with additional ability of weather predicting. This model should be able to predict how the weather might be in the future, might be one hour or even one day later. Accordingly, it is possible to calculate how much amount of electricity is potentially able to be produced during the predicting period. If it is a surplus we can activate battery into charging mode; otherwise, battery can be set to discharged mode.

Electricity Consumption Habit Prediction with Machine Learning
As we mentioned above, human tend to have similar habit of using electricity. That is to say, it is feasible to introduce machine learning technique to predict the potential demand at a specific time. According to the prediction, the system is able to know how many amount of electricity is needed in a period of time previously. This information can also be utilized to calculate how many amount of electricity is needed from grid, because we already know the amount of power might be produced in next time step, based on weather prediction and battery remaining power.

Battery Scheduling Algorithm
Based on the previous predicting model, battery controller is able to utilize these information for changing the battery mode between charge and discharge at different time period to come up with the lowest total cost.

Here are some factors consist in this algorithm

$$Unit\ Price\ at\ time\ t = f_{price}(t)$$

$$Demand\ at\ time\ t = D(t)$$

$$Solar\ Generation\ at\ time\ t = G(t)$$

The total amount needed from power grid could be represent by the following equation,

$$D_{grid} = \sum_{t=i}^{j} G(t) - D(t)$$

If D_{grid} is larger than 0, that means there are surplus that could be stored into battery. On the other hand, if D_{grid} is less than 0, that means this home needs power supplied from grid network.

If this home require some power supply from grid between time period i to j, the cost could be represented by the following equation,

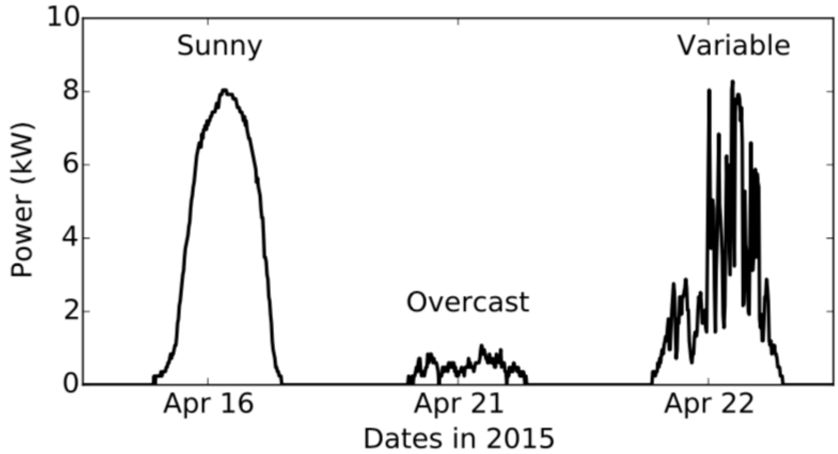
$$Cost(i, j) = \sum_{t=i}^{j} [G(t) - D(t)] \times f_{price}(t)$$

The goal of this algorithm is to find the lowest cost in specific period time, which could be represented as,

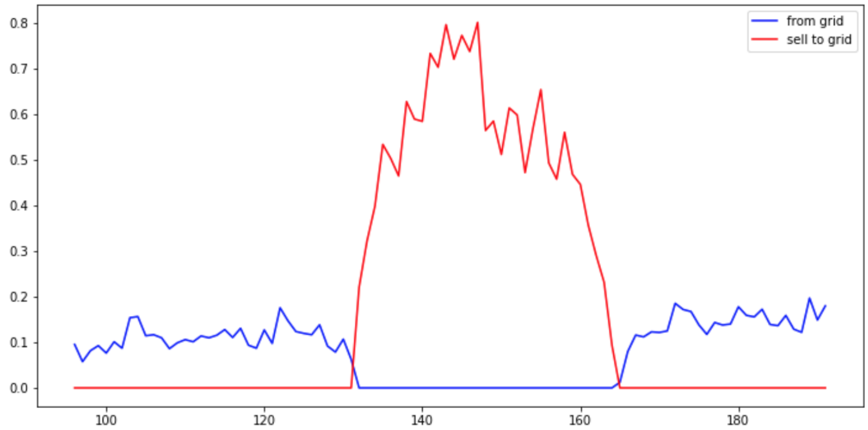
$$ArgMin\ Cost(i, j)$$

5 Solar Power Production

Solar power is a pretty much weather depending resource. The producing rate dramatically affected by sun light exposure of that day. The following image shows the solar power generation of different kind of weather.

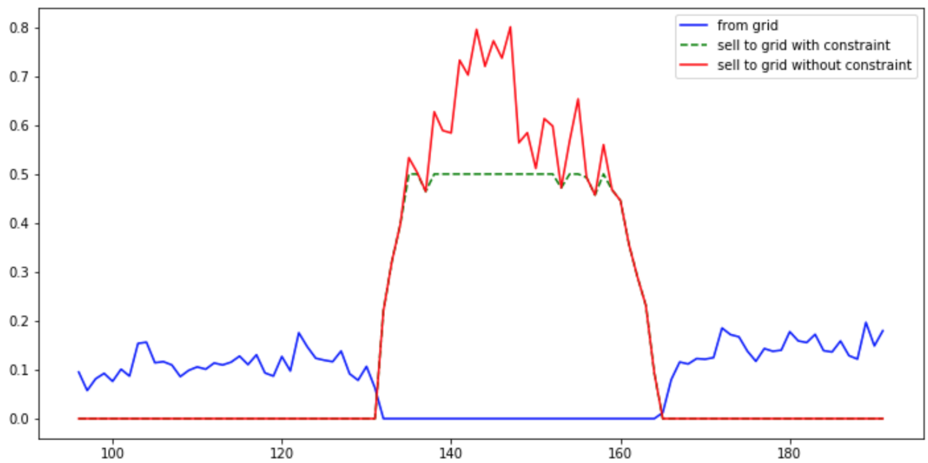


It is possible for a solar panel produce sufficient solar power for a house to use if it's a sunny day. Moreover, there might be surplus production. We are able to sell this surplus production electricity agent through power grid. On the other hand, if it's a overcast, a house could still depend on power grid when there is no sufficient solar power generated. The following image show the distribution of power utilization of a day.



6 Grid Constraint

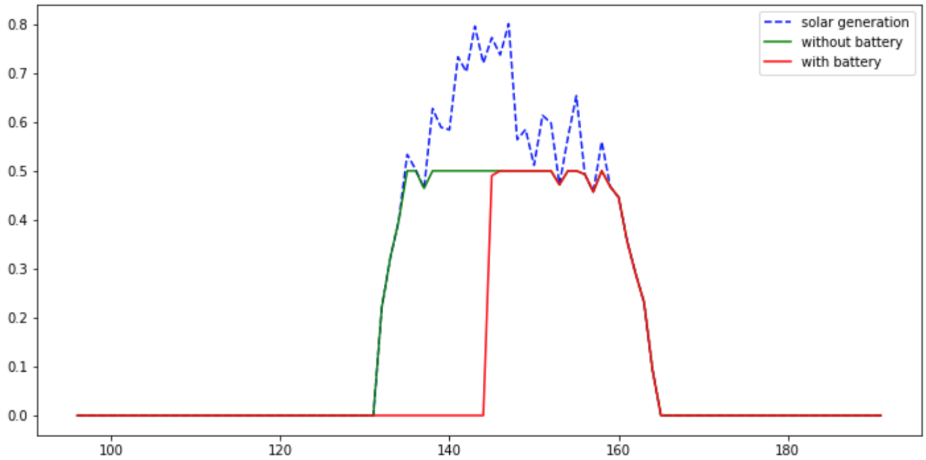
Basically, using the grid connected with every house is the best way to deal with extra solar power production. The grid has already be constructed and utility agents are connected as well. However, several issues make it somehow infeasible to let the grid to take over them. (1) Grid is always set with some limit for sending electricity back to agent due to physical limit or other constraints. Even those limits do not exist (2) agents tend to purchase those extra production with relatively lower price than they sell to people. The following image shows distribution of power utilization when the grid constraint(=0.5) is applied to grid. From the image we can found that the amount of solar power between green and red spike is wasted due to the grid constraint.



7 Battery Equipment

7.1 Solar Power Charging

One of the best way to deal with that wasted power is to store it and use it later when demand. Battery makes it possible to store solar power that is not being consumed right away. Although there's a variety kind of battery with different capability of volume, charging rate, etc, our assumption of battery is based on Tesla Powerwall if battery condition is needed to be specified. From the following image, we shows three conditions with different battery involvement and grid constraint. Compared with previous image, it's not difficult to find that the time of performing wasting power is being delayed. Moreover, the region between original solar generation and 'with battery' is relatively smaller than 'without battery'. That is to say, equipped with a battery could reduce the waste of solar surplus in a certain level.



7.2 Grid Power Charging

The above only consider the situation of charging by solar power. In that case, the battery only has its use on day time, moreover, when sunshine exposed. However, we could make more use of battery. First, we want our home unit to consume electricity from lower unit price as much as possible. Second, we don't want the battery to stay idle during period other than day time. The battery in this system assume that it's able to being charged by grid power.

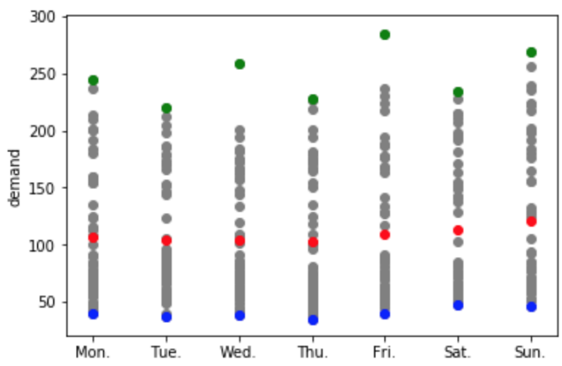
8 Battery Scheduling Model

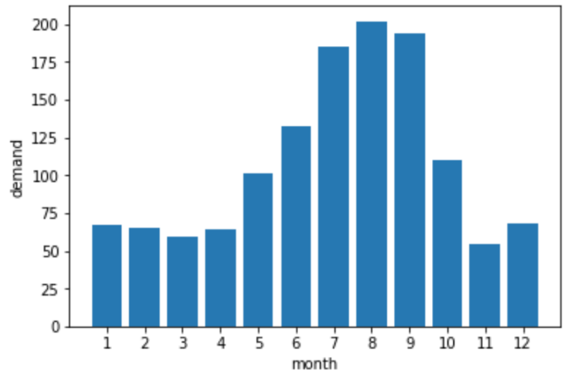
8.1 Solar Generation Predictor

The productivity of solar panel deeply related to the weather condition of that day. Based on this idea, if it's able to predict weather condition, it's probably also possible to predict the solar generation as well. The solar generation model is a regression with input of weather prediction of a day, and output the prediction of solar generation on that day. The weather data is from Texas, Austin from 11/1/2018 to 10/31/2019. Weather feature includes temperature, dew point, wind speed and humidity. After normalizing all these feature, model will these feature of one day and output a solar production of that day as output.

8.2 Demand Predictor

The usage of electricity different from not only weekday and weekend but also the month. From the following images, we can find that the usage on weekend and Friday tends to be higher. Moreover, the usage during summer also has the prone to be higher. The prediction model then based on these two features to predict demand as output. This linear regression model takes day and month as input, and predict an approximate demand on that day.





8.3 Charged-from-Grid Prediction

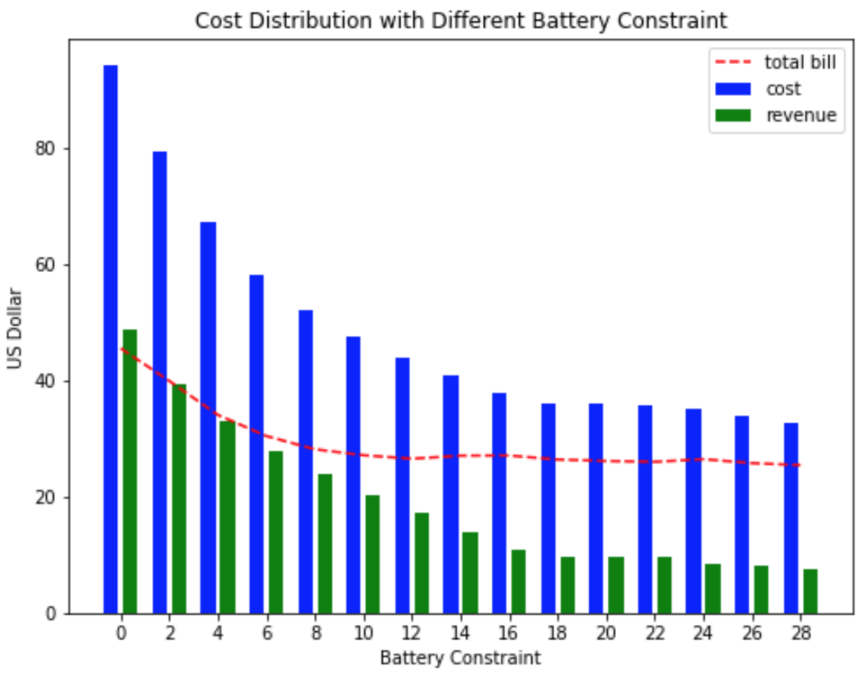
After getting both solar production prediction and demand prediction, we could also know the approximate amount of electricity require from grid on that day. Difference between demand prediction and solar prediction is the charge-from-grid prediction. Based on this prediction, the battery is charged in every time slot, which is not in high unit price, if battery is not full until total charge reach the prediction.

9 Experiment and Evaluation

During experiment, we train both demand predictor and solar predictor with data in Texas, Austin from 11/1/2018 to 10/31/2019 and do the testing with data from 11/1/2019 to 11/16/2019. The evaluation of all experiment regard to the amount of accumulated cost calculated by total cost minus revenue from selling surplus solar power to grid.

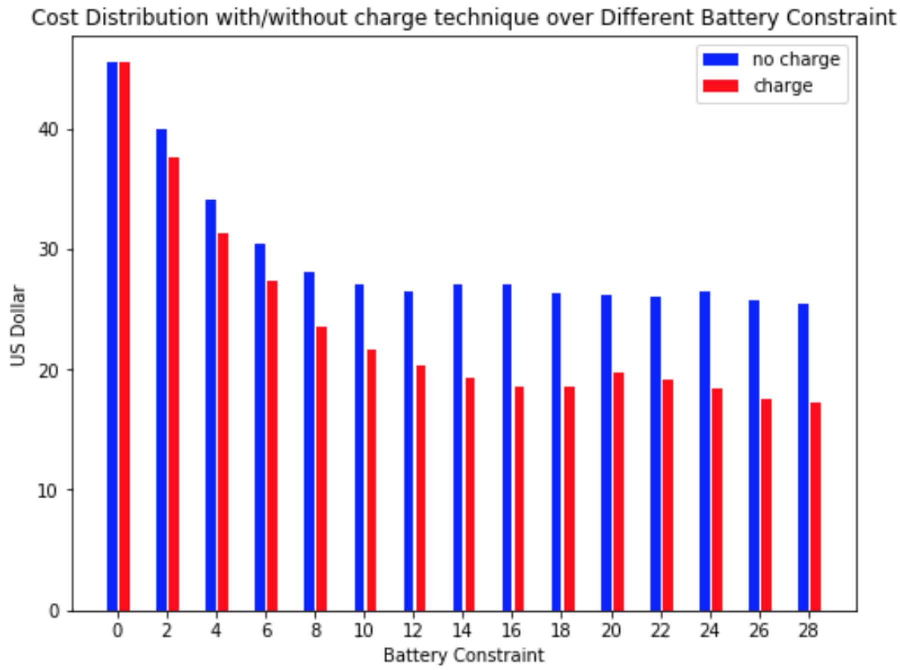
9.1 Influence of Battery Constant to Total Cost

This experiment tried to show how battery constraint (the volume of battery) will affect the cost. The red dotted line represent the accumulated total cost. The cost dramatically decrease when the battery constraint increase from 0 to 12. It's important to notice that battery constraint equals to 0 means there's no battery involved (no solar power is stored and no charge from grid). After battery constraint being larger than 12, curve of total bill tend to stay at around 30 USD. It implies that, with battery equipped, total cost will reduce for a certain amount, however, there's a margin effect on battery constraint.



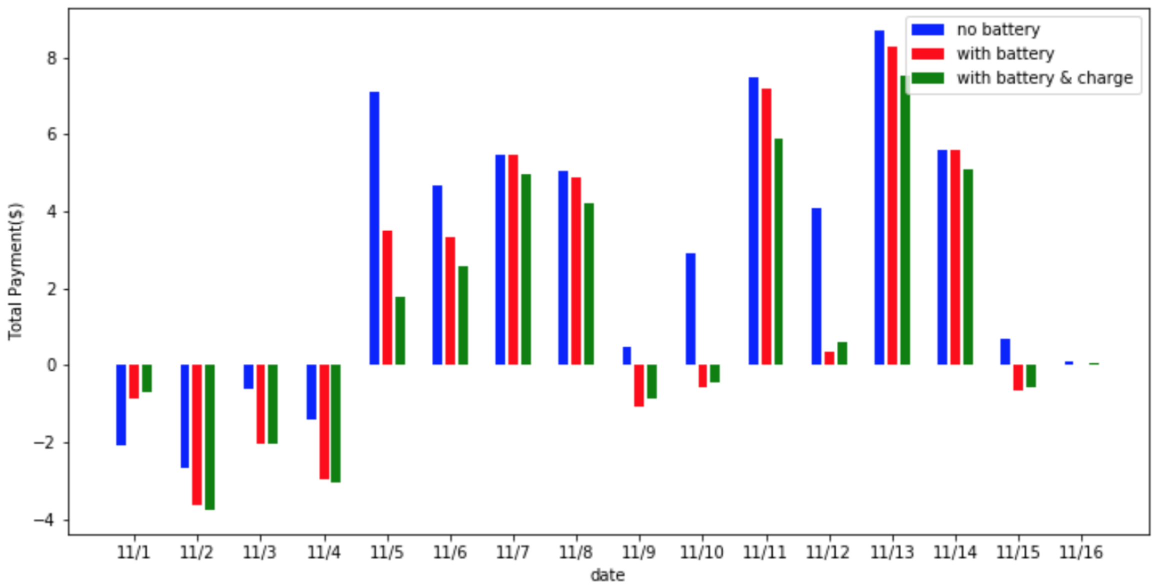
9.2 Influence of charge-with-grid to Total Cost

This experiment attempts to show the difference on cost when charge-from-grid scheduling is applied. Again, battery constraint equals to 0 means there's no battery involved. It's not difficult to see that the cost different between technique-involved and not-involved is getting larger along with the increment of battery constraint and keep stable when battery constraint reached around 14. However, every condition that charge-with-grid involved except for battery constraint = 0 cost lower.



9.3 System Deployment

In this experiment, we tried to compare the demand difference from (1) without battery and charge-with-grid system (2) with battery but without charge-with-grid system (3) with battery and charge-with-grid system. From the chart, (3) and (2) are having better performance than (1) in almost every day except from 11/1. The reason result from the performance of 11/1 is because battery was being charged on that day, the revenue was accordingly decreased. When comparing (2) and (3), the difference between them are not dramatically large. However, what to notice here is that (3) is doing better on increasing revenue income. On the other hand, (2) is doing better on saving cost.



10 Conclusion

Battery could actually help reducing the cost. By taking advantage from lower unit price period for charging, the cost actually reduced as well. However, the effectiveness of this system also affected by several constraints such as, overall weather condition of the region, battery constraints, etc. Although we do not consider those factors in this project, this system overall help people save money and better use of solar power and grid power. Moreover, due to the different merits taken from sole battery equipped and battery charging, the effectiveness may also be different.

11 Future Work

There are much more issue and constraint could take into consideration in the future. For example, dismissing rate of charging, transferring rate of consuming from battery, or adaptivity to different region.
The predicting model introduced in this system is simple and light weighted. We could try different machine learning model to predict demand and solar production. The more accurate the model has, the more accurate we could better use of solar power and charging.

12 Reference

Stephen Lee, Srinivasan Iyengar, David Irwin, Prashant Shenoy.(2017) Distributed Rate Control for Smart Solar Arrays