Final Report
Optimization Framework for Economic Operation of Solar Farm with Consideration of Variable Electricity Price

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Introduction

With exponential growth of photovoltaics between 1992 and 2018 and expectation to reach 4.7 terawatts in 2050, energy storage methods are necessary to offset the down time at nights, intermittency caused by the weather, and better control of the grid. Among different types of storage methods, Li-ion batteries provide a viable solution with high energy density, low environmental impact, and decreasing cost. Therefore, this project will focus on a solar farm with a Li-ion batteries energy storage unit as shown in Fig. 1. The control objective is to maximize the economic benefit of the solar farm given a variable electricity price. Some studies had been conducted on this hybrid system [1-3]. In this project, the battery degradation is neglected. Instead the battery cost is calculated by the depreciation. Also the battery is assumed to have 100% efficiency and no self-discharging behavior. Moreover, to protect the battery from over charged or discharged, the state of charge (SOC) is limited within the range between 20%-90% which implies that the battery output voltage is constant.

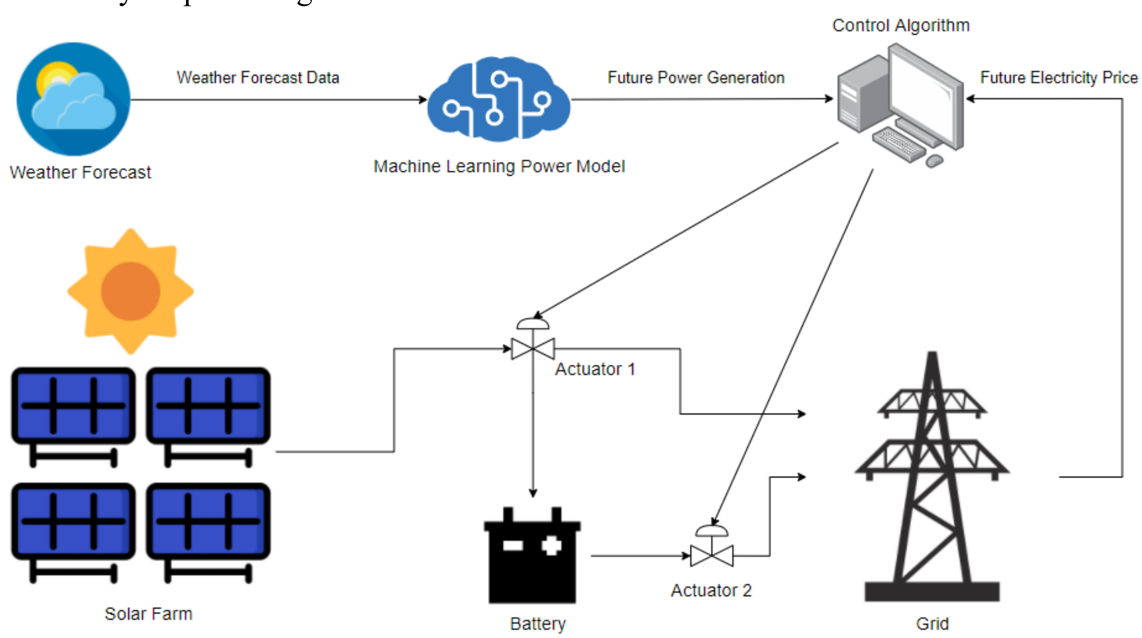

Fig 1. System Diagram

Battery Model

There are three types of Li-ion battery models, the mathematical model, the electrochemistry model, and the equivalent circuit model. The mathematical model is derived from some analogy using first-order and second-order models to describe the battery behaviors. Therefore, the mathematical model is simple but not accurate. In contrast, the electrochemistry model developed from physics results in a complicated model. For our study, we will use the equivalent circuit model which is not complicated but is accurate.

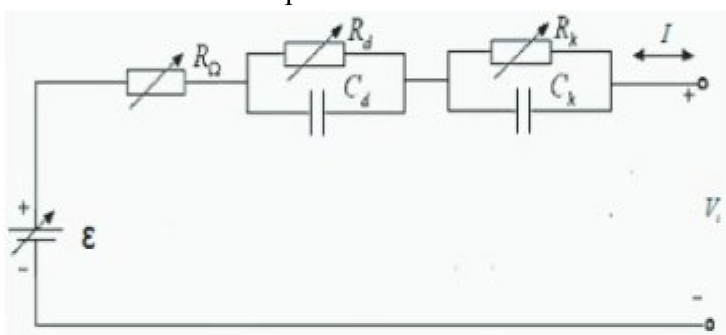

Fig 2. Configuration of the Equivalent Circuit Model

The equivalent circuit model is built by a series of capacitors and resistors. The configuration of the circuit is shown in Fig. 2. The relationship between the output voltage and the state of charge (SOC) is described as follow:

$$SOC = a\left(V_t + I(t)R_\Omega + I(t)R_d\left(1 - e^{-t/\tau_d}\right)\right) + b + k \cdot e^{1-1/[SOC(1-SOC)]} \quad \text{Eq. 1}$$

For different types of the battery, the parameters are different. To estimate the parameters' value, the real battery discharge and charging behavior are generated by an electrochemical model. Unlike the battery pack in the electric vehicle which requires high energy density, in energy storage cases, safety and cost are the major concern. Therefore, Lithium iron phosphate batteries are chosen.

To capture the discharge impact on the battery behavior, a parameter estimation on discharging at 0.5C, 1C and 2C are conducted. The parameters' value are estimated as follows:

Parameter	Value
a	9.188799994
R_Ω	-0.014967583337
R_d	0.0071229914887
τ_d	0.50912788003
b	-29.601264162

k	-2.8554516595

The simulation result are presented as follows:

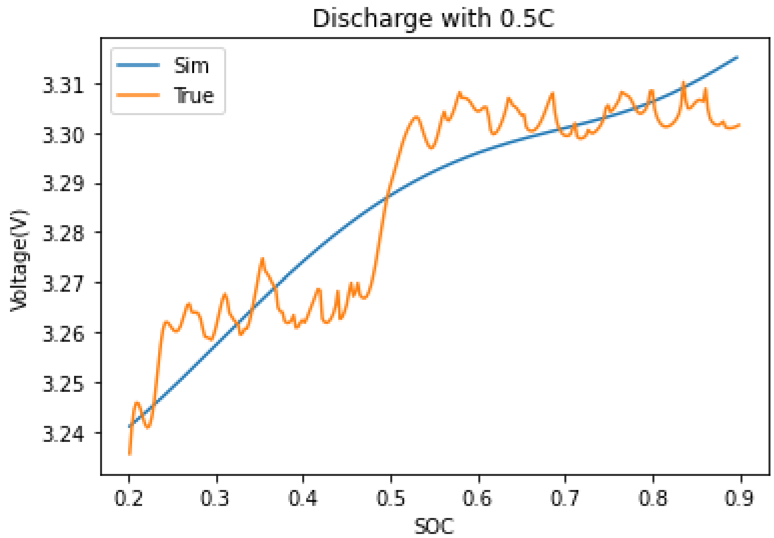

Fig. 3 Simulation vs. Real with 0.5C

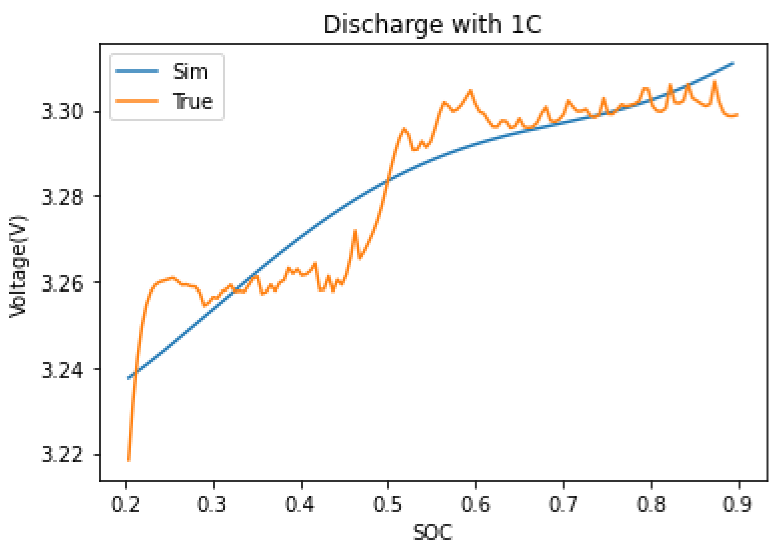

Fig. 4 Simulation vs. Real with 1C

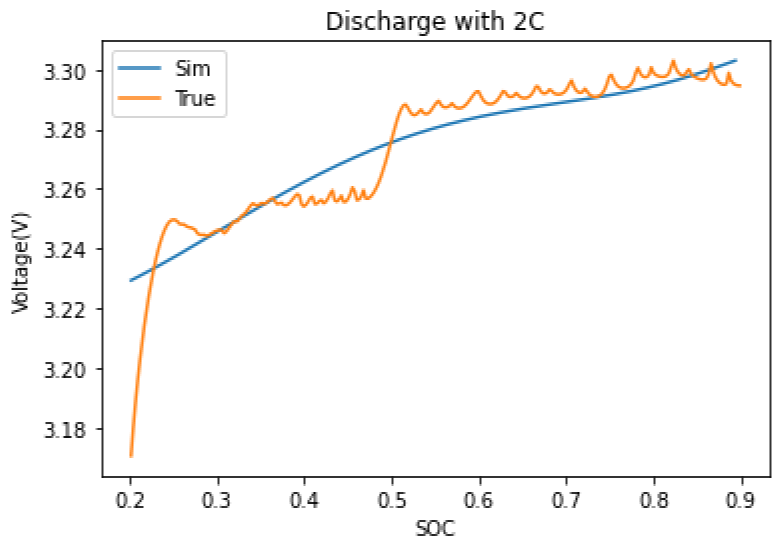

Fig.5 Simulation vs. Real with 2C

Solar Farm Model

Recently, there has been a great emphasis on reducing the carbon footprint and moving away from fossil fuels to renewable energy sources. This can be achieved through solar power plants, either implemented on rooftops or within city utility sites. The main aim of this writeup is to move to renewable solar energy by predicting the annual solar energy likely to be generated by a solar power station through local weather information.

In this study, we would like to utilize the machine learning model to predict the future solar generation for our model predictive control. Fig. 6 and Fig. 7 demonstrated that solar power generation is significantly affected by the time. Not only the solar generation will vary within a day, but also will fluctuate within a year. And these time information can be extracted from the past time series data. Therefore, in this study we utilized a long short-term memory (LSTM) neural network to process the past solar generation data and predict the future solar power generation.

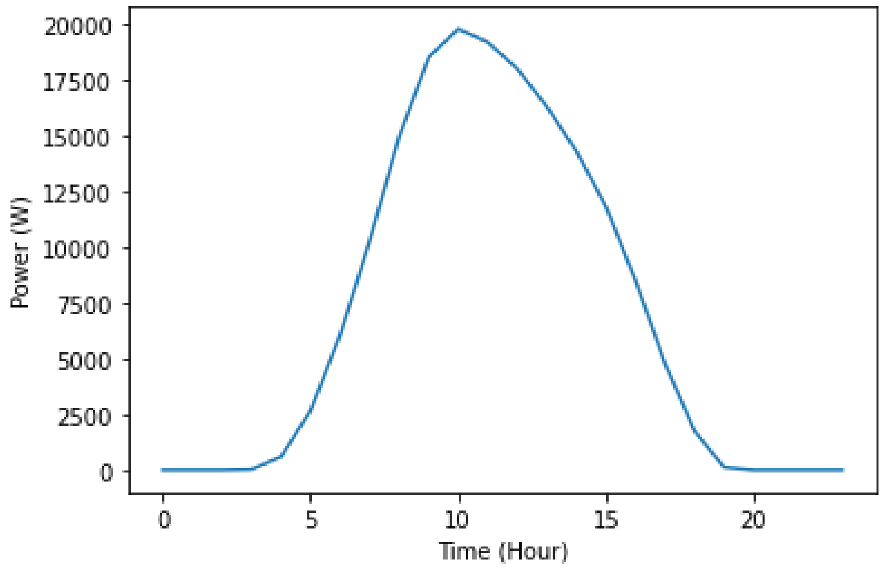

Fig. 6 Solar Power vs. Time

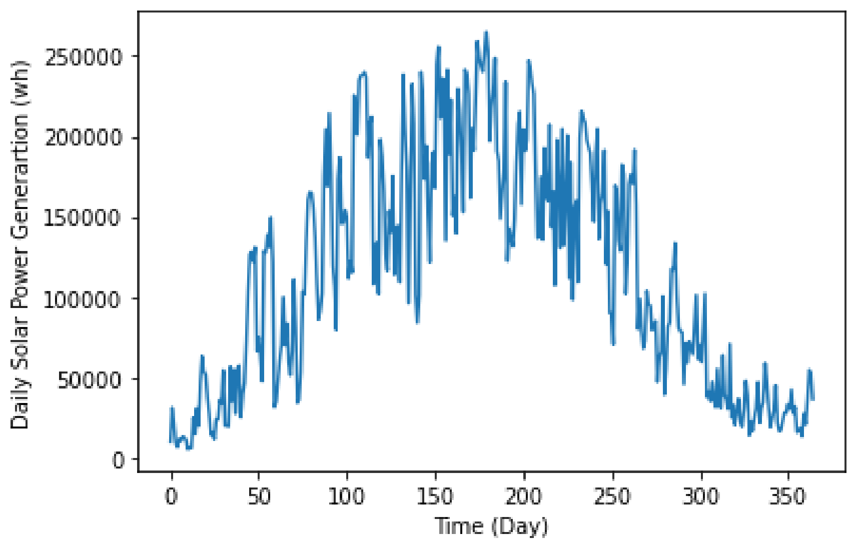

Fig. 7 Daily Solar Generation vs. Time

	Transparency	Solar Generation	Solar Capacity	Month	Day	Hour
0	42254.95	0.0	47480	1	1	0.0
4	40984.90	0.0	47480	1	1	1.0
8	39042.55	0.0	47480	1	1	2.0
12	38761.12	0.0	47480	1	1	3.0
16	38958.22	0.0	47480	1	1	4.0

Fig.8 Sample Data

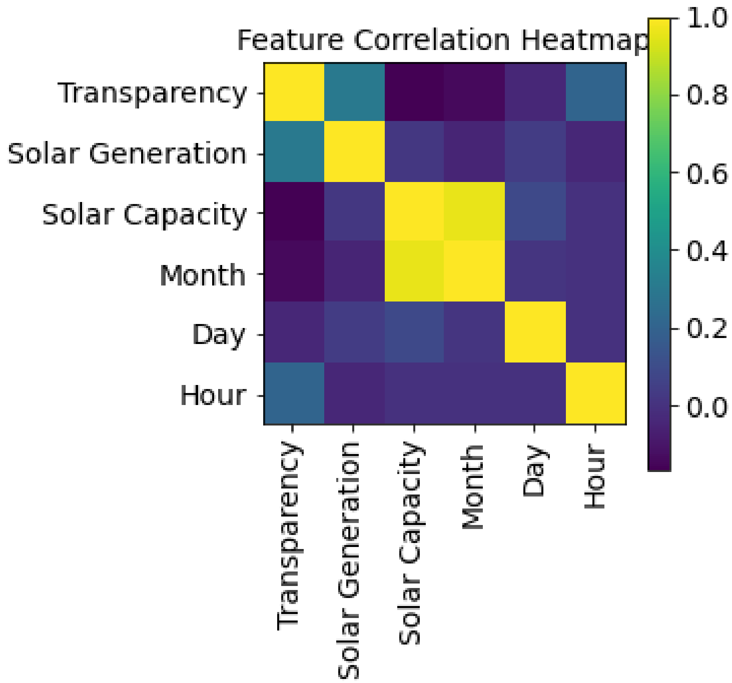

Fig.9 Features' Correlation

Fig. 8 demonstrated the sample data which contains 6 features, the transparency, solar generation, solar capacity, month, day and hour. The features' correlation are shown in Fig. 9 which indicates that the solar generation is related, from strong to weak, with the transparency, day, solar capacity, moth, day and hour. Therefore, we only consider the top 3 important features which are transparency, solar capacity and the past solar generation.

In this study we used the past 5 days' data to train the neural network. 70% of the 2019 data is used to train, and rest is used to test the data. Before feeding the training dataset to the neural network, a scalar is applied to the dataset to scale all the features into 0-1. The reason why we need a scaler is that the transparency data is significantly larger than other features. Without scaling, large input values (e.g. transparency) can result in a model that learns large weight values. A model with large weight values is often unstable, meaning that it may suffer from poor performance during learning and sensitivity to input values resulting in higher generalization error. Fig. 10 shown a prediction vs. actual for a 24hr period.

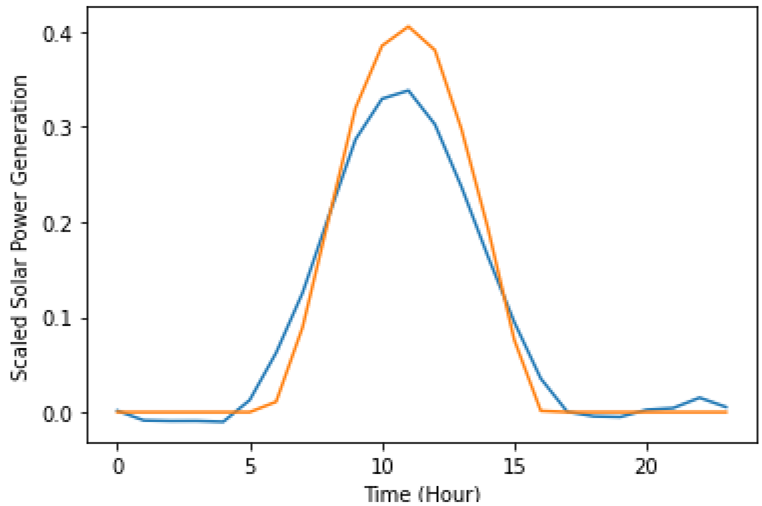

Fig. 10. Predicted vs. Actual Solar Power Generation

Model Predictive Control

To account for the future information, such as the solar power generation and the electricity price, model predictive control is introduced to control the charging behavior of the battery.

The objective of this project is to maximize the economic benefit of the solar farm by selling the electricity to the grid at a proper time. Therefore, the objective of the model predictive control is formulated as:

$$\max_{U,P_{Bat}} \sum_{t}^{N} E_t\left(P_{Grid,t} + P_{Bat,t}\right) \text{ Eq. 2}$$

where E_t is the electricity price at time t, U is the fraction of the solar energy output used to charge the battery, $P_{Bat,t}$ is the battery output to the grid at time t. The objective is to find the optimal $U^*=\{u^*_1, u^*_2, \ldots, u^*_N\}$ and $P^*_{Bat} = \{P^*_{Bat,1}, P^*_{Bat,2}, \ldots, P^*_{Bat,N}\}$ to maximize the total profit generated within timespan N.

In this study, we assume that within a same battery pack, every cell is identical to each other. Therefore, instead of modelling every cell within the battery pack, we only need to model one cell to represent others. The second assumption is that we neglect the thermal behavior of the battery. In real world, during charge and discharge, due to the internal resistance, the battery pack's temperature will change. However, in our case, the battery pack is stationary and used as energy storage, we assume that there will be a thermal control system to maintain the battery's temperature to prevent thermal runaway. The battery behaviors are described by following equations:

$$\frac{dSOC}{dt} = \frac{I_t}{C_{cell}} \text{ Eq.3}$$

$$I_t = \frac{P_{solar,t}u_t - P_{Bat,t}}{N_{cell}v_t} \text{ Eq.4}$$

$$SOC_t = a\left[V_t + I_t R_\Omega + I_t R_d\left(1 - e^{-t/\tau}\right)\right] + b + ke^{1-\frac{1}{SOC_t(1-SOC_t)}} \text{ Eq.5}$$

where SOC_t is the state of charge of the battery at time t, It is the current for each battery at time t, C_{cell} is the capacity of each individual cell, $P_{solar,t}$ is the solar generation at time t, v_t is the voltage at time t. In this study, we applied coulomb counting to keep track of the state of charge.

For battery, over-discharged and over-charged will not only significantly impact the battery's lifespan but also raise safety concern. To avoid this situation, the SOC are imposed following constraint:

$$0.2 \le SOC_t \le 0.9$$

For the battery output, we assume that the battery can only discharge to the grid,

$$P_{Bat,t} \ge 0$$

Battery Sizing

Before performing a specific study, we need to determine the battery pack's capacity. Fig. 11 and Fig. 12 shown the distribution of the daily solar power generation. To balancing the economic and feasibility, the battery pack's capacity is set based on the median value of the data which is 113774 Wh or 34900 Ah.

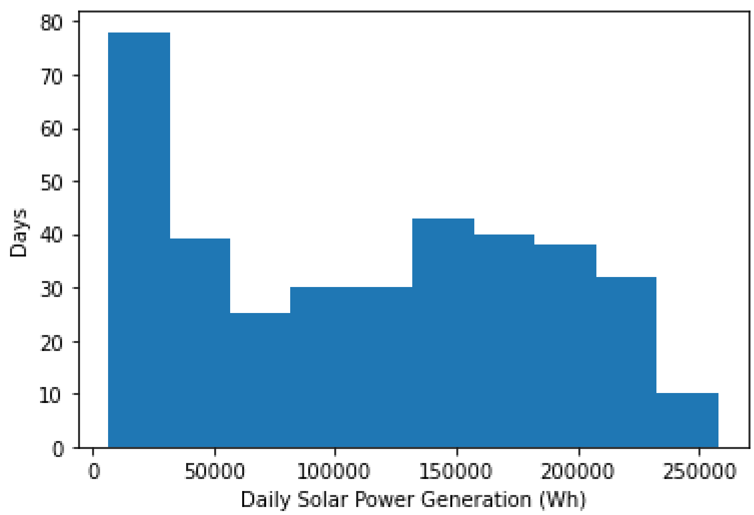

Fig. 11. Distribution Plot of the Daily Solar Generation

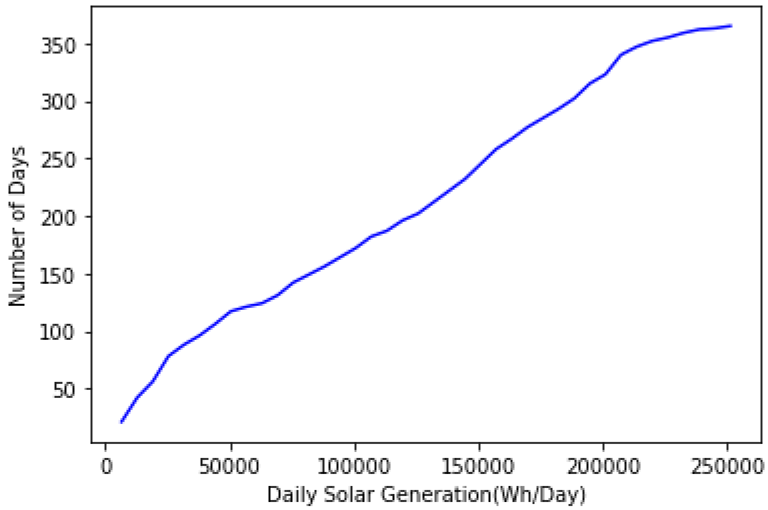

Fig. 11. Cumulative Plot of the Daily Solar Generation

Result

The results of the optimization control are presented in this section. Fig. 12 demonstrates the daily solar revenue with the model predictive control vs. without the model control. Regardless of the time, the MPC can increase the daily revenue as high as around 800% which is significant. One reason is the electricity price will fluctuate so that by storing the generated electricity at low market price and selling it at high price can elevate the revenue. The other reason is due to the characteristic of the electricity price and solar power. During the daytime, while the solar generation is increasing, the electricity price is decreasing. Without storage unit, most of the energy is sold when the electricity price is low. This further decrease the performance when there is no storage unit.

Another interesting fact is, the performance increase brought by the MPC is fluctuated within a year, lower increase during summer and higher increase in other months. The reason behind this is that during the summertime, due to the longer daytime and high solar intensity, more solar energy is generated, Fig. 7, the battery, which sized based on the median, cannot store all the solar energy to sell it in later time. Therefore, some energy is sold directly to the grid result in poor performance.

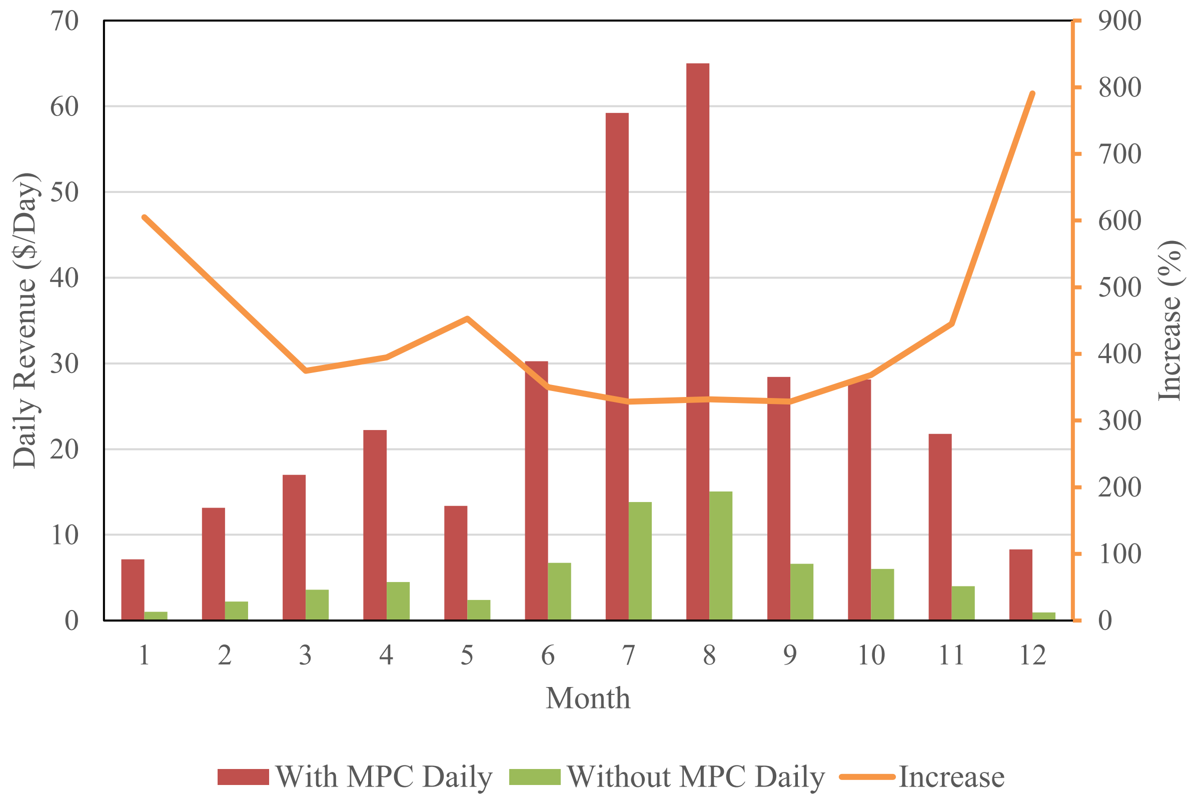

Fig. 12 Model Predictive Control impact on Daily Revenue vs. Month

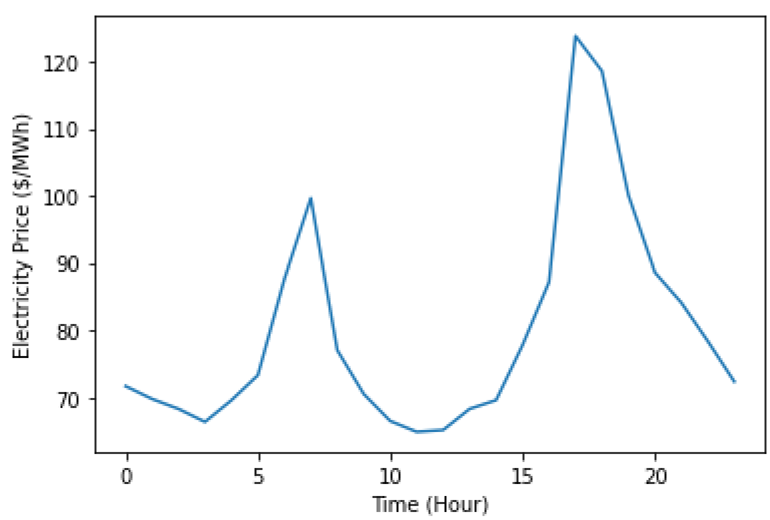

Fig. 13. Electricity Price changes with Time within a Day

Discussion of the Current

The current will significantly impact the behavior of the lithium-ion battery. With higher discharge current, less stored power can be released due to the increasing internal resistant under high current ratio. Moreover, it can also be results in safety concern and significantly shorten the lifespan of the battery. Fig. 14 shows that without current constraint the MPC model will try to release as much as it had when the electricity price is high resulting in high current ratio which is detrimental to the battery and even to the whole solar farm.

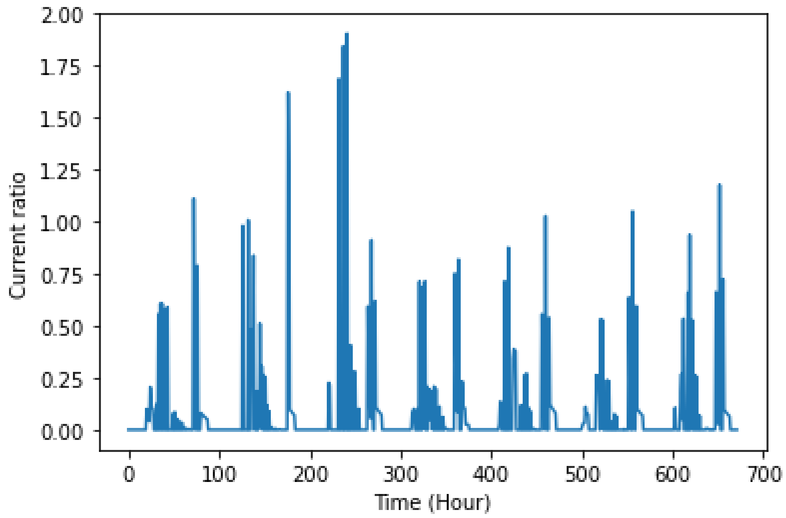

Fig. 14. Current ratio vs Time

With the concern of the current ratio, we would like to introduce a heterogeneous battery pack system as shown in Fig. 15.

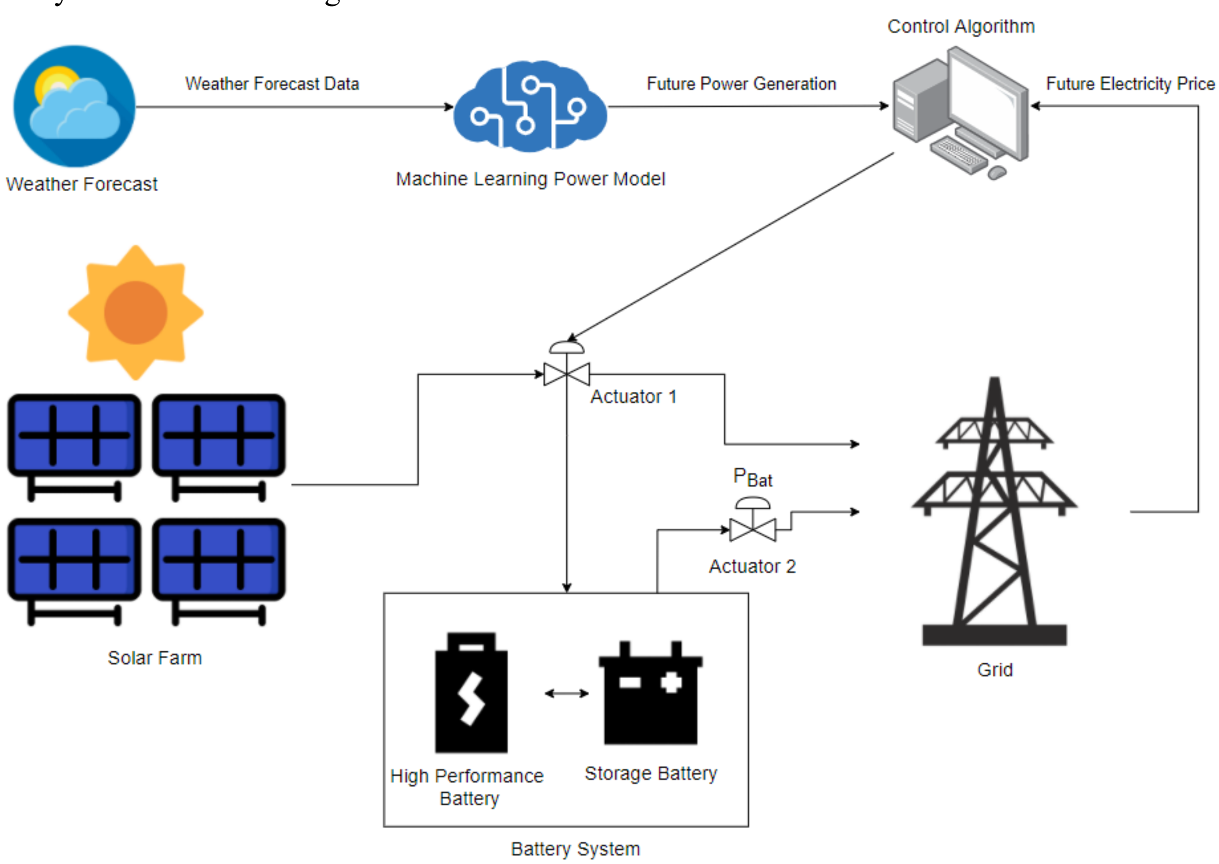

Fig. 15. Modified System

Compared with Fig. 1 which the battery is comprised only a battery pack, in this modified system, the battery pack is made with two battery pack: a high-performance battery pack, and a general battery pack. Both battery pack are connected to the solar farm and to the grid. And they are also interconnected so that the electricity can be transfer from one battery to the other. In this case, we assume that the high-performance battery can accept up to 2C current and the general battery can only accept up to 0.5C current. The optimal decision variables can be found by solving following problem:

$$\max_{U, P_{Bat}, X, P_{Bat,H}, P_{Bat,G}, P_{trans}} \sum_{t}^{N} E_t \left(P_{Grid,t} + P_{Bat,t} \right)$$

$$\frac{dSOC_{H,t}}{dt} = \frac{I_{H,t}}{C_{cell}}$$

$$I_{H,t} = \frac{P_{solar,t} u_t x_t - P_{Bat,H,t} - P_{trans,t}}{V_{H,t}}$$

$$SOC_{H,t} = a\left[V_{H,t} + \frac{I_{H,t}}{C_{cell}} R_{\Omega} + \frac{I_{H,t}}{C_{cell}} R_d \left(1 - e^{-t/\tau}\right) \right] + b + ke^{1-\frac{1}{SOC_{H,t}\left(1-SOC_{H,t}\right)}}$$

$$\frac{dSOC_{G,t}}{dt} = \frac{I_{G,t}}{C_{cell}}$$

$$I_{G,t} = \frac{P_{solar,t} u_t \left(1 - x_t\right) - P_{Bat,G} + P_{trans,t}}{V_{G,t}}$$

$$SOC_{G,t} = a\left[V_{G,t} + \frac{I_{G,t}}{C_{cell}} R_{\Omega} + \frac{I_{G,t}}{C_{cell}} R_d \left(1 - e^{-t/\tau}\right) \right] + b + ke^{1-\frac{1}{SOC_{G,t}\left(1-SOC_{G,t}\right)}}$$

$$P_{Bat,t} = P_{Bat,G,t} + P_{Bat,H,t}$$

$$P_{Grid,t} = P_{solar,t}\left(1 - u_t\right)$$

$$I_{H,t} \in \left[-2, 2\right]$$

$$I_{G,t} \in \left[-0.5, 0.5\right]$$

$$SOC_{G,t}, SOC_{H,t} \in \left[0.2, 0.9\right]$$

$$P_{Bat,G,t}, P_{Bat,H,t} \geq 0$$

where $SOC_{H,t}$, $I_{H,t}$, $V_{H,t}$, and $P_{Bat,H,t}$ are the SOC, current, voltage, and output power to the grid of high performance battery at time t, $SOC_{G,t}$, $I_{G,t}$, $V_{G,t}$, and $P_{Bat,G,t}$ are the SOC, current, voltage, and output power to the grid of general battery at time t. In this study, we will assume that the high-performance battery and the storage battery share the same SOC-Voltage behavior and have the same cell capacity. The only difference is the maximum current ratio. $P_{trans,t}$ denotes the power transfer between the two types of battery.

Result of Heterogeneous Battery Pack

Before compared to the homogeneous battery pack's performance, we need to determine the ratio of the high-performance battery. In this study, we assume that the unit price of the high-performance battery is 25% higher than the general battery. Therefore, a study on economic performance with different ratio of the higher performance battery is carried out below:

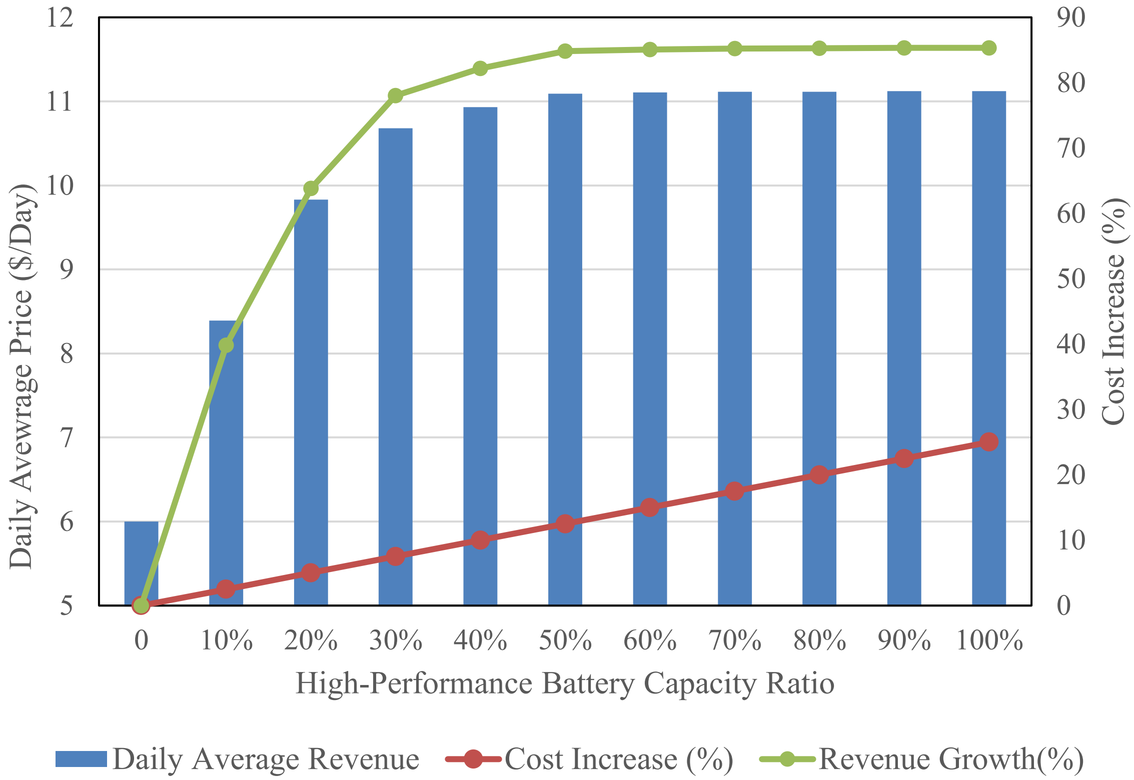

Fig. 16. Economic Performance with Different High-Performance Battery Capacity Ratio

According to Fig. 16, as the capacity of the high-performance battery increases, the daily renvenue of the solar farm increase which caused by discharging more power into grid during the high electricity price. In the meantime, the cost also increase due to the expensive high-performance battery. From Fig. 16, we can tell that after the high-performance battery capacity higher than 50%, the revenue stop to growth. Therefore, from economic perspecitve, it is wise to choose the high-performance battery capacity ratio lower than 50%.

Summary

In this study, we propose to use model predictive control to improve the solar farm economic performance. Without considering the current limit, the MPC can elevate the daily to $26/Day from $5.57/Day with about 466%. However, due to the concern of the battery's safety, we set the current limit of the general battery pack to 0.5C, which decrease the daily revenue to $6.02/Day. To deal with the rapid discharge during the high electricity price, we introduce the heterogeneous which comprise the general battery and high-performance battery. The latter one can discharge at 2C. Before 50%, the daily revenue will growth as the ratio increase. With 50%, the daily revenue reach \$11/day which is about 200% and 83% increase compared to without MPC control and battery pack comprised of general battery.