May 2022

Model Predictive Control for Grid Scale PV and Battery

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MODEL PREDICTIVE CONTROL FOR GRID SCALE PV AND BATTERY

by

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A Thesis Submitted in

Partial Fulfillment of the

Requirements for the Degree of

Master of Science

in Engineering

at

The University of Wisconsin-Milwaukee

May 2022

ABSTRACT

MODEL PREDICTIVE CONTROL FOR GRID SCALE PV AND BATTERY

by

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The University of Wisconsin-Milwaukee, 2022
Under the Supervision of Professor Brian Armstrong

Model Predictive Control (MPC) is a control technique that uses prediction data to optimize costs over a given predictive horizon. There are many papers that use this technique to optimize cost in a substantially loaded microgrid, but these techniques are not feasible for utility-scale PV+Storage facility. In this study, MPC is used to optimize the cost for a utility-scale PV+Storage facility, by adding a factor of a possible curtailment. The thesis also presents the various factors that the MPC has in that utility size grid. These factors include line losses, net yield, and curtailment.

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LIST OF ABBREVIATIONS

PSCG	Photovoltaic + Storage + Control + Grid
PV	Photovoltaic
SOC	State of Charge
MILP	Mixed Integer Linear Programming
MPC	Model Predictive Control
SBC	Scheduled Battery Control
ROI	Return on Investment

ACKNOWLEDGEMNTS

First, I would like to thank my advisor, Dr. Brian Armstrong, for the extensive knowledge that I have gained through our conversations over the past few years. Your insightful feedback, questions, and attention to details have sharpened the way I approach any problem.

Mom and dad, words can't express how much appreciation I have for you both. Thank you for all the support sacrifices and unconditional love. You both are my inspiration, and I hope to be half as levelheaded, understanding, calm and peaceful as you are.

Thank you to DNVGL for providing Synergi Electric licenses, and to WE Energies for providing data to build the PSCG Simulator.

Thank you to GRid-connected Advanced Power Electronic Systems (GRAPES) and NSF for grants and support for the work of the PSCG simulation and completion of this thesis. Also, a thank you to Harvey Scribner of Southwest Power Pool for supporting the project with expertise.

I would also like to thank the High-Performance Computing team at UW-Milwaukee, Darin Peetz and Daniel C Siercks, for assisting me in using Mortimer.

To Dr. Turney and team at Johnson Controls, I am very grateful for the internship and the knowledge gained throughout my time there.

I would also like to thank all my professors at UW-Milwaukee that have encouraged and supported me in every step of my academic career.

To all my peers in IEEE and EWB, I am very grateful for countless conversations, that have shaped me into the person I am today.

Getting to my thesis required more than academic support, and I would like to thank all my friends and family for the love, care and moral support and for making sure I was always happy and healthy.

1 Introduction

The utilization of renewable energy has been increasing in general due to rising concerns of global warming and depleting oil/gas reserves. Solar energy is the most abundant and accessible source of all the current renewable energy resources. This has compelled policy makers around the world to encourage installation of Photovoltaic (PV) systems. These systems need a lot of land, so most of the utility-scale facilities are in remote areas. In 2019, 5,400 MW of utility-scale PV was installed in the US, accounting for 60% of new PV installations [1]. As the size and number of utility-scale solar installations grows, rural sites served by relatively weak feeders become more important.

As a result of the irregular nature of solar irradiation, power management strategy (PMS) becomes complex. An imbalance of dynamic power demand and the PV generation is a major challenge. As of late, the battery energy storage system (BESS) has been used in combination with a PV system to address this concern. Utility-scale PV facilities also require an energy storage system, and both the PV installation and battery are a major investment. Advanced control strategies, such as Model Predictive Control, are important for maximizing the Return on Investment, while minimizing the negative grid impacts possible with intermittent distributed generation.

In this thesis, a Photovoltaic + Storage + Control + Grid (PSCG) simulator is used, which gets real feeder data from WE Energies [2], real solar irradiance data, real load data, real utility prices in order simulate the behavior of PV and storage facility of choice. The simulation is built using

Synergi Electric, utility modeling software provided by DNVGL, and uses feeder data provided by WE Energies to provide accurate site-specific results, as opposed to the more commonly used IEEE standard bus model or Reliability Test System (RTS) model [1]. To enable modeling novel control strategies, Synergi Electric is used to build a database, which is referenced while running the PSCG simulation.

In the facility size, the sizing of the battery is based on the combined battery power electronics [kW] and the duration [hours] to give total energy in the battery[kWh]. The PV is sized by the maximum generation[kW]. For example, a facility with 4000kW PV power, 1000kW battery power, and 2-hour duration has a total battery energy would be 2000kWh, while the PV's maximum generation power is at 4000kW.

1.1 Motivation

Throughout the research for revenue optimization of PV + Battery systems, most papers just compare the Model Predictive Control's revenue to another algorithm such as a rule base control.

This thesis, however, examines other aspects of the systems that are changed by the implementation on Model Predictive Control, while increasing the Return on Investment. The baseline used for comparisons is a schedule-based battery control algorithm.

Curtailment is largely driven by mismatches between PV output and load. In the PSCG Simulator the maximum selling power is considered as a load, the battery charging power and power electronic losses are considered as loads. The MPC algorithms used in many papers show in section 2.3 consider a Mixed Integer Linear Programming (MILP) which adheres to the PV and Battery constraints. However, these papers lack a curtailment possibility in their equations

since most of them are modeled for microgrid systems. At utility-scale PV+Battery systems, this could lead to no feasible solutions in the MILP calculations.

Among the papers researched, none consider Return on Investment (ROI) and facility pricing as a metric for viability. This study uses current pricing of PV and battery storage as well as current energy pricing.

1.2 Thesis Contribution

The thesis contribution can be shown in 4 different areas:

- Development of a Model Predictive Control algorithm that maximizes ROI (by considering market prices variation, irregular nature of solar irradiation and power electronic loads) and minimizes PV Curtailment while adapting to the constraints of the PV and battery maximum powers.
- Validation to ensure that the result that the MPC + MILP algorithm calculates is optimal. To do this, a small variation from the MPC results was placed at each time step and executed for the predicted horizon to check if any variation gives a better result. This validation also ensures that all the power electronic and battery constraints and load requirements are met.
- Analysis of how Model Predictive Control can effect other aspects of the PSCG (such as battery charge and discharge losses, line losses, curtailment) when compared to a Scheduled Battery Control method.
- Raised questions to be included in the Model Predictive Control algorithm such as battery life, grid limit, power electronics losses.

1.3 Outline

The thesis is divided into five main sections:

- Introduction

  The introduction sets up the motivation to work on this thesis, along with an quick view of contributions made in this paper.

- Background

  The background section reviews the background literature, reviewing various methods and tools that contribute to this thesis, which include background of Model Predictive Control in Photovoltaic systems, Curtailment, analysis of Return on Investments and cost variation of PV, and battery installations.

- Body

  The body section includes the implementation of methods that were researched in the background section. This includes Model Predictive Control, Mixed Integer Linear Programming and solar irradiance upsampling.

- Results

  The results section includes the profits shown by the implementation of Model Predictive Control, along with the analysis of the changes that Model Predictive Control causes in the PSCG Simulator.

- Future Work

  The analysis of the effects that MPC has on the utility scale PSCG system has led to possibilities of improvement of various parameters such as line losses and curtailment. These are explained with a possible technique that could be explored in the future.

2 Background

2.1 PSCG Simulator and Synergi Electric

Synergi Electric is a commercial distribution system modeling software utilized around the world and provided by DNVGL. It simulates, analyzes, and plans power distribution feeders, networks and substations [1].It can contain thousands of elements in a single feeder model and can model feeder-wide impacts such as low and high voltages, losses, load tap changer operation, and load flows. Additionally, Synergi Electric is validated by over 30 years of industry experience.

A feeder model provided by WE Energies (WE Energies, Personal communication, 2019-2021), shown in Figure 2-2, gives real feeder data for a Wisconsin grid to be used by Synergi Electric for the PSCG simulation. The PSCG simulation utilizes a database built from Synergi Electric's Time Series Analysis tool to produce a high-fidelity, high-resolution modeling of PV and storage deployments [2]. The simulation flow, shown in Figure 2-1 gives a visual representation of how PSCG operates.

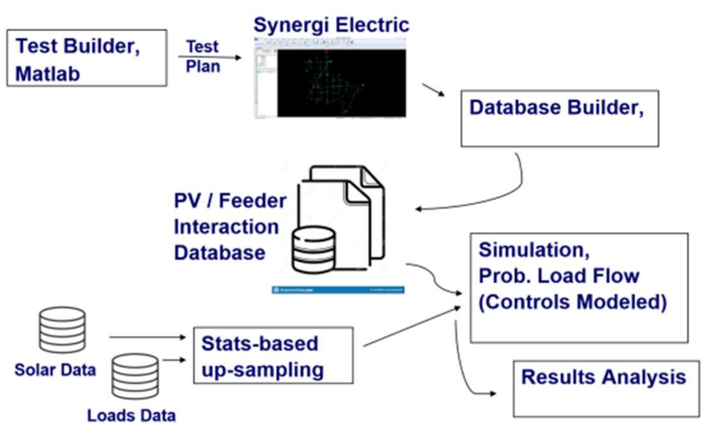

Figure 2-1 : Photovoltaic Storage + Control Grid simulation flow with Synergi Electric integration [1].

The results from Synergi Electric, comprised of voltages at the substation and segments throughout the feeder, loading on segments throughout the feeder, and feeder-wide losses, are used to build a feeder interaction database. This database, once built, is then used repeatedly within the PSCG simulation to determine voltage and up to 28 other variables based on real and reactive power at the PV and storage facility and feeder load [1].

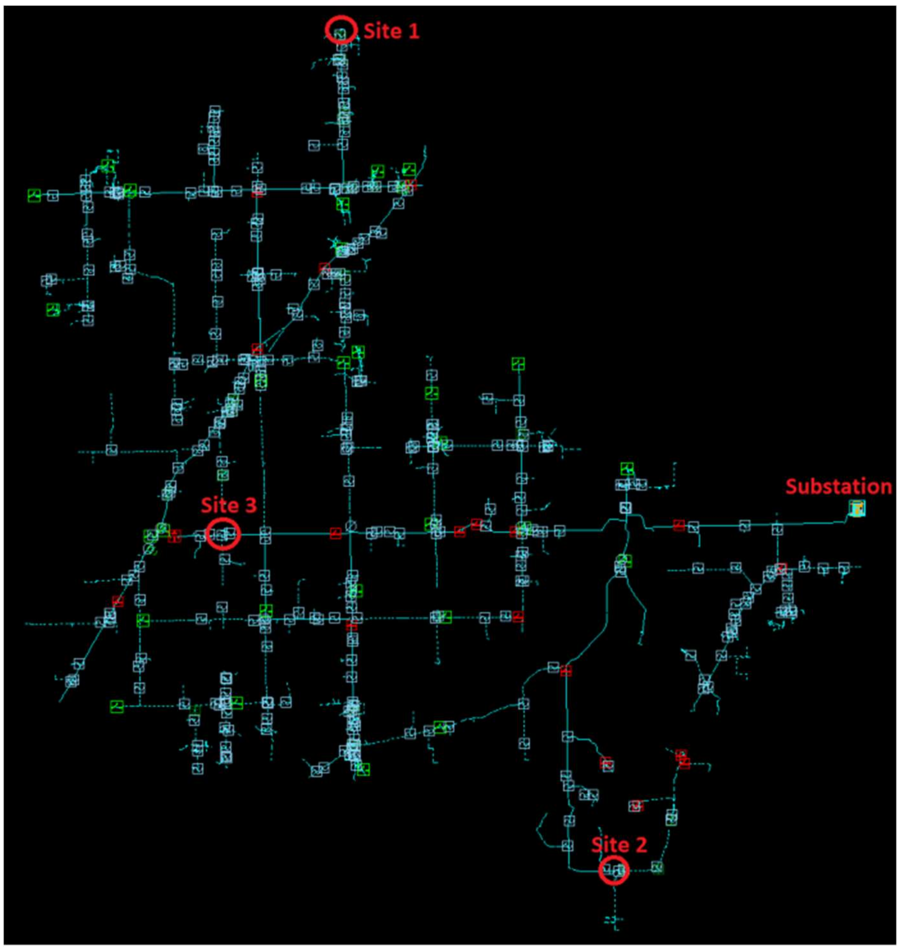

Figure 2-2: Synergi Electric feeder model provided by WE Energies of a real Wisconsin grid [1].The simulator in this primarily uses site 1 for analysis.

2.2 PV/Battery pricing

2.2.1 Battery Pricing

Battery prices, specifically lithium-ion, have decreased 88% in the last decade, with the last three years being approximately 14% per year [4]. This is driven, in part, the increase in renewable energy use, especially solar. Figure 2-5 shows the forecast of battery pricing to continue to decrease to almost 50% of the current values in the next several years.

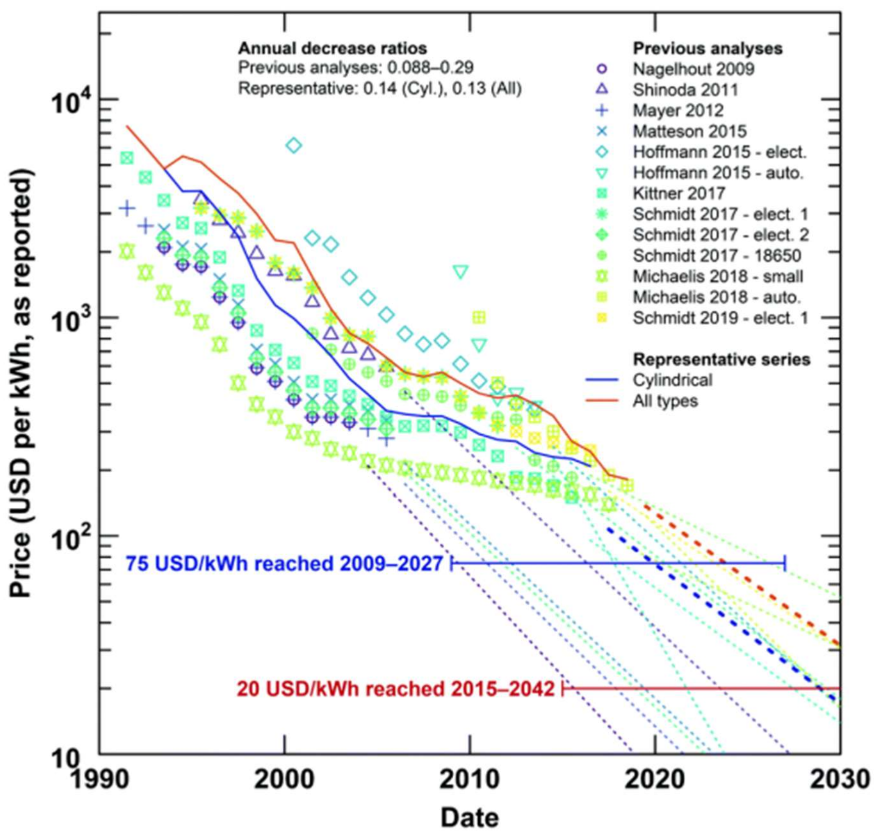

Figure 2-3: Lithium-ion cell price data and forecast based on simple extrapolation using the data since 1990. Annual decrease ranges frim 8.8% to 29% [6].

2.2.2 PV Pricing

Along with the battery, the PV cost has also decreased 81% in the last decade with consistent 13-18% yearly decreases over the last few years, shown in Figure 2-4. This is also due to demand of solar energy facilities, which is caused by increase in policies in favor of renewable energies. [6,7]

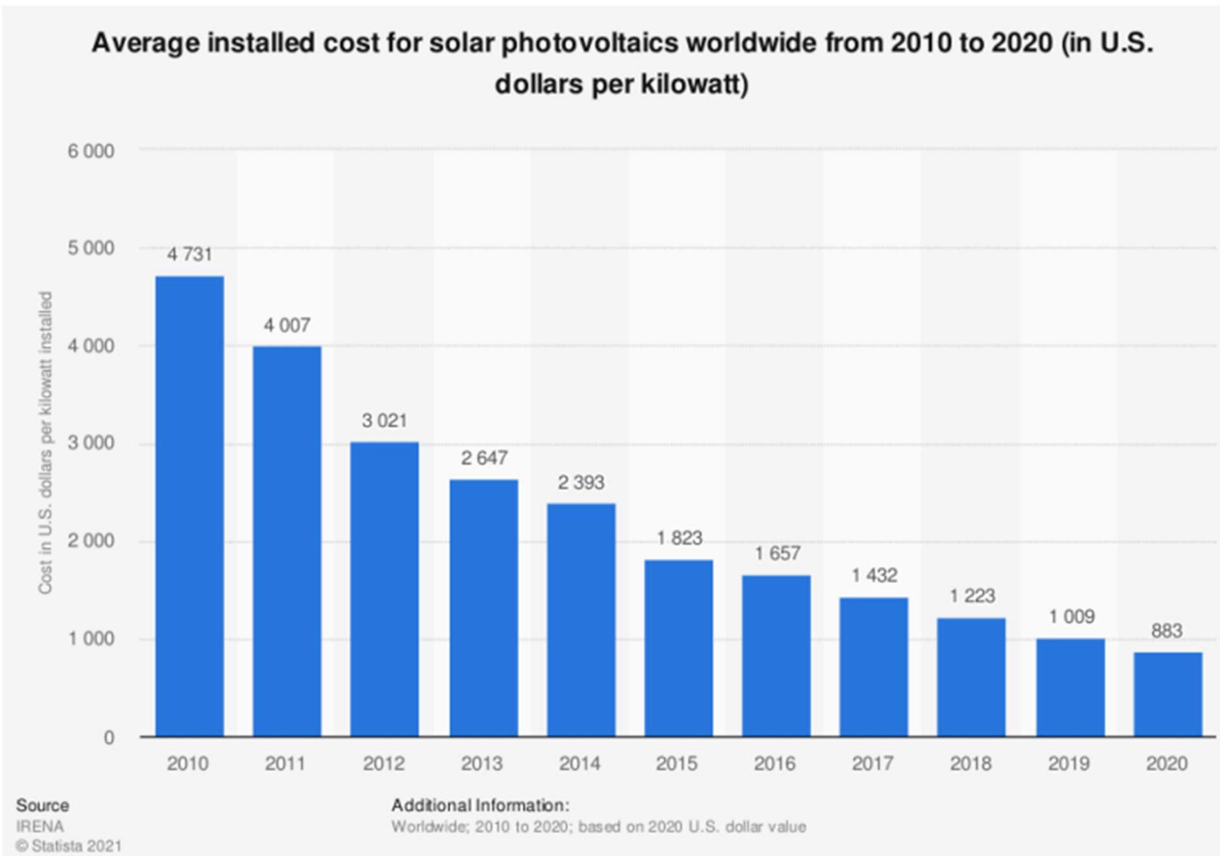

Figure 2-4 : Between 2010 and 2020, the average installed cost for photovoltaics worldwide has declined steadily due to widespread availability of materials making it cheaper to produce. In 2020, the average installed cost of solar PV systems was 883 U.S. dollars per kilowatt [5].

2.3 MPC Strategies in Microgrids

There has been extensive research for microgrid control strategies due to the complexity of the problem [10,14,15,19].” The capability of handling constraints in a systematic way makes MPC a very attractive control design methodology in those applications where a process is required to work in wide operating regions and close to the boundary of admissible states and inputs” [36]. This has motivated the study of alternative MPC approaches, requiring the solution of simpler optimization problems in real time.

Bonthu *et al.* [10] present a Model Predictive Control (MPC) approach based on the Mixed Integer Linear Programming (MILP) to develop an optimal power management strategy (PMS). Their cost function was formulated to minimize the electricity bill of a commercial building. Many studies related to the cost optimization techniques concentrate on a PMS between distributed generation, BESS and connected loads for minimizing the total electricity cost, improving generation efficiency, saving energy and stabilizing the power system.

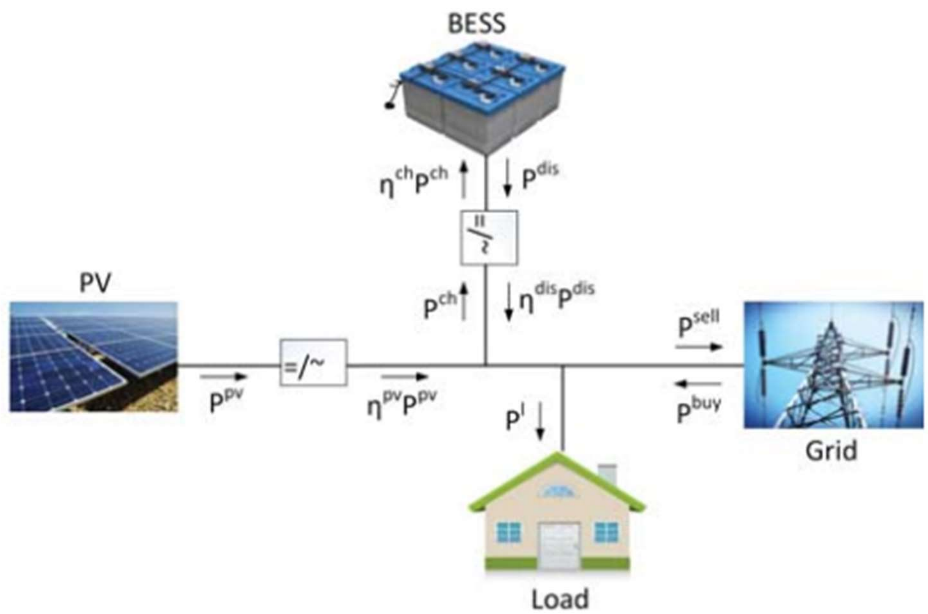

Figure 2-5: Substantially loaded microgrid used in Bonthu *et al.* modeled to minimize buying cost for a residential building.

Parisio *et al.* explore energy management solutions by applying a Model Predictive Control approach that consider fixed power conversion loss which makes the problem unrealistic. In [10], MPC methodology is applied to tackle the dynamic economic problem, aimed at minimizing the generation cost over a finite time horizon.

Many sources such as [9,10,11,12], centered the long-term objectives on the efficient utilization of renewable energy by designing the BESS schedule to store the electricity locally generated from renewable sources and reuse it during peak load demand periods. Within this research, it is observed that the formulation of achieving maximum revenue into a Mixed Integer Linear Programming (MILP) optimization problem with time-varying constraints has been

addressed in various capacities, however it was only either addressed in microgrids or to optimize cost for a commercial building.

MILP frequently uses the branch-and bound algorithm which gives the global optimum solution with minimum computational time, this approach can be applied to complex models. [13]. Bonthu *et al.* proposed MILP-MPC for dealing with dynamic control and state constraints while satisfying performance specifications. This control strategy provides advantages in terms of feedback control technique to predict the future response of the plant over a finite horizon, incorporates constraints explicitly, is easy to formulate as a constrained optimization problem, and provides closed-loop stability and inherent robustness [10].

The objective function and constraints are formulated into a finite-time optimal control problem. At each sampling period, a set of system states are updated, the optimal control problem is solved, and the controller time horizon recedes by another step. According to Bonthu *et al.* [9], there are no current models including power electronic converters with consideration of dynamic efficiencies. Their systems have shown a 24% increase in total revenue with the MPC-MILP algorithm.

The mathematical programming, heuristics, and constraints that are formulated for substantially loaded microgrid in *Bonthu et al.*[10] could be infeasible in utility-scale PV+Storage facilities, as the formulas do not include the possibility of curtailment. The cause of curtailment in PV systems is further explained in section 2.4.3.

2.3.1 Mixed Integer Linear Programming

In Marzband *et al.*, the authors have used a Mixed Integer Nonlinear Programming method (MINLP) in their execution of Model Predictive Control since they deal with a microgrid operational management problem [15]. This includes policies for controllable loads (demand side

management), interaction with the utility grid and storage models, which are both continuous (charge/discharge rates and buy/sell rates) and discrete (on/off states for distributed generator) [16,17]. Although PSCG has dynamics for controllable loads and interaction with the utility grid and storage models, it only requires continuous (storage charge/discharge rates and grid buy/sell rates) decision variables for the revenue optimization MPC Algorithm. This makes the problem a MILP (Mixed Integer Linear Programming). Silvente, Javier, *et al.* employ a MPC method in their algorithm which also employs MILP. The branch-and-bound techniques are mostly applied to MILP problems. The main advantage of the branch and bound method is that, if a solution is reached, the solution is known to be globally optimal [18].

2.3.2 MILP in Matlab

The PSCG Simulator is built in Matlab, so an optimization tool in Matlab can be used to evaluate the MILP. MATLAB's intlinprog routine serves this purpose. Kuendee *et al.*layout the six basic strategies that are used by intlinprog [36]:

- Reduce the problem size using linear program preprocessing
- Solve an initial constraint-relaxes(non-integer) problem using linear programming
- Perform mixed-integer program preprocessing to tighten the LP relaxation of the mixed-integer problem.
- Use Cutting-plane method to further tighten the LP relaxation of the mixed-integer problem as shown in Figure 2-6.
- Try to find integer-feasible solutions using heuristics.
- Use a branch and bound algorithm to search systematically for the optimum solution.

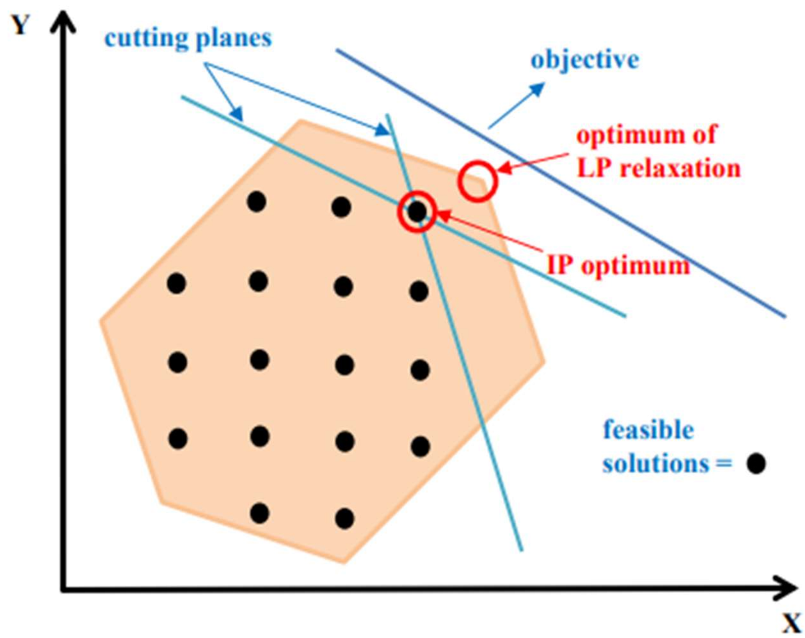

Figure 2-6 : Cutting-plane method used in MATLAB’s intlinprog function [36].

2.4 PSCG Parameters/Variables

2.4.1 Return on Investment

The Return on Investment (ROI) indicator was introduced to provide a numerical quantification of the revenue that the facility receives from an energy source, in terms of how much revenue is made from an energy production process compared to how much is invested on the equipment.

Renewable electricity generation technologies provide only a small percentage of global electricity generation, but their market share is growing steadily. Particularly, the installed photovoltaic (PV) capacity has undergone a major increase over the last five years according to Kautto and Jaeger-Waldau . [24] Increased market penetration of PV technologies recently has also occurred with incremental improvements in their environmental performance. The relative

performance of PV in terms of ROI, however, has so far been impaired by a dearth of clearly defined and consistently framed comparative studies. Several published studies have indicated PV and wind as having often discouragingly low ROI, when compared to conventional fossil-based energy [25]. An increase in ROI is advantageous for the utility-scale PV+Battery systems owners.

2.4.2 Battery charge discharge frequencies

The distributed generation by PV can improve network load carrying capabilities, reduce losses in long distribution lines and improve their voltage profile. However, when PV penetration level is too high, the phenomena of excessive reverse power flow, overvoltage's along distribution lines and general power quality problems have been observed [27]. The negative aspects of distributed generation can be mitigated by the battery energy storage system. Therefore, the battery storage might become more common for grid–connected PV systems and such solutions have recently appeared on the market. The lead-acid batteries are still the cheapest reliable technology for household energy storage. The operation in the grid-connected PV-system, however, puts very specific requirements for battery life when self-consumption is the priority.

The simulation in Marańda *et al.*uses the data of commercial batteries with cycle service life shown in Figure 2-7 [26]. In general, the capacity decreases with number of cycles and depth-of-discharge (DoD).

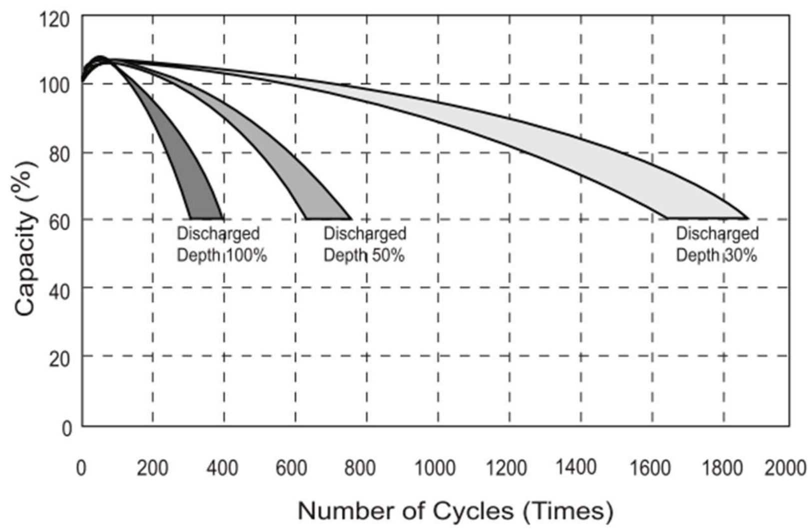

Figure 2-7: Battery capacity degradation represents the number of cycles for 3 values of discharge depth [26].

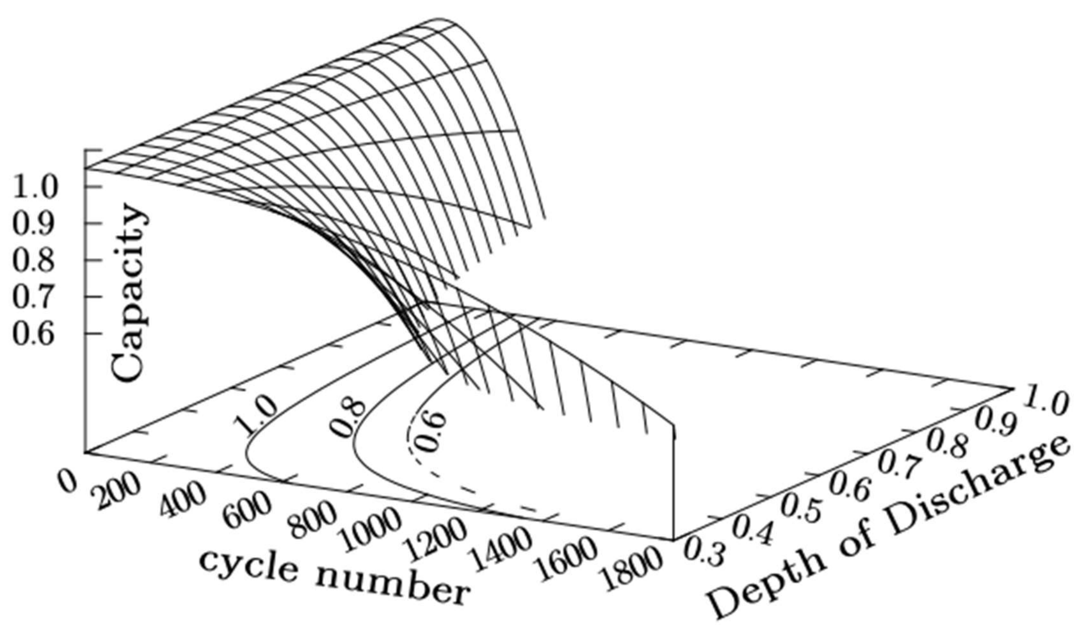

Figure 2-8 : The inputs of number of cycles and Depth of discharge have been fitted by the capacity function in Marańda *et al.* to obtain continuous capacity function shown in this 3D representation of battery capacity degradation [26].

2.4.3 Curtailment

Fuel-based generator's unused output represents fuel that can be burned to generate output later. However, with PV+Battery systems, the unused output represents available electricity that is lost forever [28]. This also is considered in other renewable energy sources, such as wind energy. Most PV curtailment stems from system constraints that impede the grid from absorbing more PV output. This occurs when the PV power is higher that all the consumption powers (selling, charging, and loads).

There is often a mismatch between when PV output is available (midday) and when that output can be absorbed by the grid. This is shown in Figure 2-9 for multiple renewable energy systems. On that day, the PV output peak occurred in the midday when demand was too low to absorb the output.

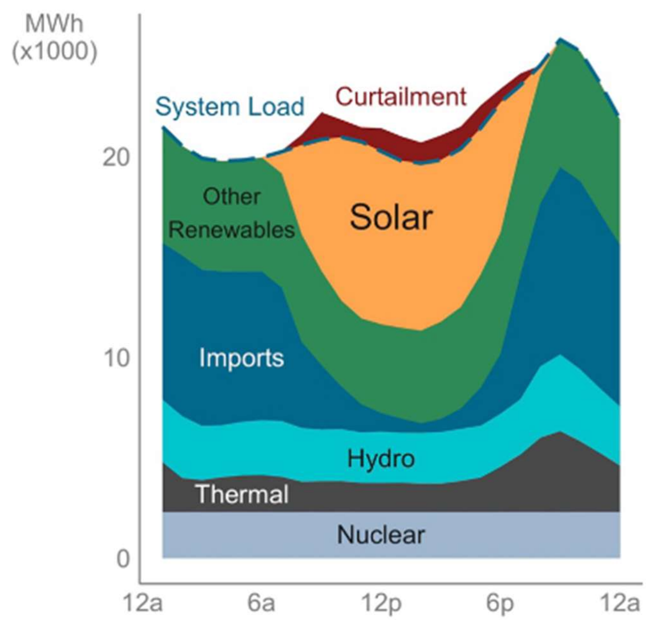

Figure 2-9: Photovoltaic curtailment event on May 13, 2018 compared to multiple renewable energy systems in California. [28].

2.5 Solar irradiance modeling

Solar panels rely on semiconductor cells producing photo-current from sunlight. The solar panels are dependent on their exposure to the sun as well as the PV cell temperatures. This points to the importance of modeling the solar irradiance of the area where the PV and storage facility is to be located. The amount of energy produced is proportional to the radiation that reaches the panel, solar irradiance [31]. There are three different aspects of solar irradiation considered in PV effectiveness:

1. Direct Normal Irradiance (DNI) - direct radiation that reaches a panel and is of interest to concentrated solar that would track the sun's position, maximizing captured radiation.
2. Diffuse Horizontal Irradiance (DHI) - DHI is a scattered irradiation which is due to the sky and fractional cloud cover.
3. Global Horizontal Irradiance (GHI) - GHI is a combination of DNI and DHI for a horizontal panel such as a photovoltaic

The upsampling of the solar irradiance can be done by simply interpolating between the GHI points. However, this does not consider the high-frequency cloud cover since the short-term changes of the solar irradiance dramatically affect power generation [32]. A battery can help to smooth out cloud cover changes, but it is desirable to model the solar irradiance on the same time scale as the simulation to accurately simulate the real PV response. Since the GHI is proportionate to the amount of cloud cover, okta is a prime method to simplify the approach to upsampling the solar irradiance data. Okta is a representation of cloud cover in 9 increments, from 0 to 8, with 0 being completely clear and 8 being completely covered by cloud. According to J.M. Bright *et al.*, Okta value is considered an acceptable representation of obscured irradiance

[33]. Among many stochastic approaches to upsampling solar data, a Markov chain is well established as an acceptable method for modeling solar irradiance. Figure 2-10 shows the comparison of Clear sky GHI to a Resampled GHI that was produced for a site that is used in the PSCG Simulator.

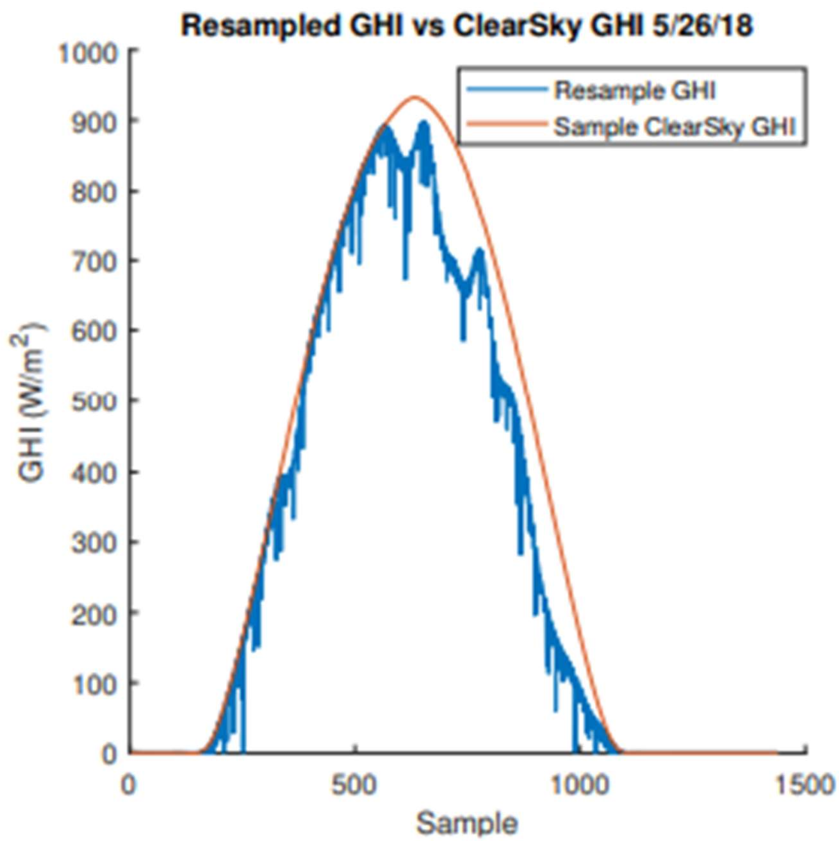

Figure 2-10: Global Horizontal Irradiance upsampled for a day in the simulator using Markov chain with okta value representation [2]. Each sample represents one minute.

3 Body

3.1 Improvements to MPC from *Bonthu et al.*'s paper

The Model Predictive Controller developed for the PSCG simulator is primarily adapted from Bonthu *et al.*[10]. As mentioned previously, the PSCG simulator is based on a utility -scale PV system, and Bonthu's is based on substantially loaded microgrid system. This could raise the issue of curtailment when the PV generation is higher than the loads and power consumption in the simulator. Since the MPC-MILP formulation in Bonthu's paper does not allow the PV to curtail, the controller turned out to be infeasible at high PV times.

There was also an error in formulation of their lower-level bounds for charging power, discharge power, selling power and buying power. According to the bounds presented in the paper, the minimum charge rate is 0.12kW and minimum discharging rate is 0.02kW. This communicates and forces MILP to find a solution where the charging and discharging can take place at the same time which is not physically possible. These lower bounds for each variable have to be set to 0.

3.2 Model Predictive Controller

In this work, the goal of the Model Predictive Controller in PSCG is to maximize the ROI. For this case, a slotted time approach is used, whereby 2 days is divided into N discrete time intervals and each interval with a duration of Ts (e.g., N = 96(48 hours) for Ts = 30 minutes (0.5 hours)). In order to maintain a good battery life as specified in section 2.4.2 , a good range should be considered for the charging/discharging operation. In this case, following Bonthu *et al.*[9], SoC_{min} was set to 20% while SoC_{max} was set to 80%.

The battery is restricted with the maximum allowable amount of power flowing in/out during charging/discharging, respectively. These inequalities are modeled in equations (3-5) - (3-6).

δ_b the binary variable to decide between charging and discharging.

$$\delta_b = \begin{cases} 0\ for\ charging \\ 1\ for\ discharging \end{cases}$$

The maximum buying power and selling power represent the capacity of the grid. The inequalities for these are shown in equations (3-7) and (3-8).

δ_g the binary variable to decide between charging and discharging.

$$\delta_g = \begin{cases} 0\ for\ selling\ energy \\ \quad 1\ for\ buying\ energy \end{cases}$$

Since the simulator is for utility scale, a curtailment variable ($P^{curtail}$) has been added and the only constraint is it must be positive. The $P_{max}^{curtail}$ is set to ∞.

The MILP-MPC strategy depends on the predicted values of PV Generation, load demand, and the buy rates and sell rates. The program used to evaluate the equation (3-1) is *intlinprog.* Intlinprog use the matrices formulated in equations (3-11) – (3-15) to evaluate the minimal cost. The MPC Controller is updated at every sample step in the PSCG simulator, and the control values are predicted for that prediction horizon.

The PSCG Simulator ensures that all the constraints are met and updates the state of charge every minute based on the control outputs of the Model Predictive Controller. The updated State of Charge is then used in the next sample step of MPC.

Constants

P_{max}^{buy}	maximum allowable buying power from grid [kW]
P_{max}^{dis}	maximum allowable charging power [kW]
P_{max}^{dis}	maximum allowable discharging power [kW]
P_{max}^{sell}	maximum allowable selling power to grid [kW]
SoC_{max}	upper limit of state-of-charge (%)
SoC_{min}	lower limit of state-of-charge (%)
T_s	discrete time interval duration

Decision Variables

δ^b	binary variable for charging/discharging power from/to BESS
δ^g	binary variable for buying/selling power from/to facility
P^{buy}	power bought from the grid [kW]
P^{ch}	power exchanged with BESS during charging [kW]
P^{dis}	power exchanged with BESS during discharging [kW]
P^{sell}	power sold to the grid [kW]
$P^{curtail}$	power that can be curtailed [kW]

Other parameters used in the formulation

η^{ch}	Battery charging efficiency
η^{dis}	Battery discharging efficiency

η^{pv}	efficiency of PV system connected converter
c^{tou}	Price of buying energy [$\frac{\$}{kWh}$]
c^{f}	Price of selling energy [$\frac{\$}{kWh}$]
P^{l}	load power demand [kW]
P^{pv}	power generation from PV system [kW]
SoC_k	state-of-charge (%)

Table 3-1: Nomenclature for the MPC Algorithm.

$$\min_u f^T u \qquad subject\ to \begin{cases} \delta_b\ and\ \delta_g\ are\ integers \\ A_{ineq} \cdot u \le b_{ineq} \\ A_{eq} \cdot u = b_{eq} \\ lb \le u \le ub \end{cases} \tag{3-1}$$

$$J = \min_u \sum_{k=0}^{N-1} (c_k^{tou} P_k^{buy}\ T_s - c_k^{tou} P_k^{sell} T_s) \tag{3-2}$$

$$U = \left[P^{dis}\ \ P^{ch}\ \ P^{buy}\ \ P^{sell}\ \ P^{curtail}\ \ \delta^b\ \delta^g \right]$$

Battery Interactions

$$SoC_{k+1} = SoC_k + T_s \eta_k^{ch} P_k^{ch} - T_s \eta_k^{dis} P_k^{dis} \tag{3-3}$$

$$SoC_{min} \le SoC_k \le SoC_{max} \tag{3-4}$$

$$0 \le P_k^{ch} \le \left(1 - \delta_k^b\right) \cdot P_{\max}^{ch} \tag{3-5}$$

$$0 \le P_k^{dis} \le \left(\delta_k^b\right) \cdot P_{max}^{dis} \tag{3-6}$$

Grid Interactions

$$0 \leq P_k^{sell} \leq \left(1-\delta_k^g\right) \cdot P_{max}^{sell} \tag{3-7}$$

$$0 \leq P_k^{buy} \leq \left(\delta_k^g\right) \cdot P_{max}^{buy} \tag{3-8}$$

$$0 \leq P_k^{curtail} \leq P_{max}^{curtail} \tag{3-9}$$

Energy Equations:

$$\eta_k^{pv} P_k^{pv} + \eta_k^{dis} P_k^{dis} + P_k^{buy} - \left(P_k^{sell} + P_k^{ch} + P_k^{l} + P^{curtail}\right) = 0 \tag{3-10}$$

$$A_{ineq} = \begin{bmatrix} I & 0 & 0 & 0 & 0 & -P_{max}^{dis}\, I & 0 \\ 0 & I & 0 & 0 & 0 & P_{max}^{ch}\, I & 0 \\ 0 & 0 & I & 0 & 0 & 0 & -P_{max}^{buy}\, I \\ 0 & 0 & 0 & I & 0 & 0 & P_{max}^{sell}\, I \\ T_s\eta_k^{dis} & -T_s\eta_k^{ch} & 0 & 0 & 0 & 0 & 0 \\ -T_s\eta_k^{dis} & T_s\eta_k^{ch} & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{3-11}$$

$$b_{ineq} = \begin{bmatrix} 0 \\ P_{max}^{ch} \\ 0 \\ P_{max}^{sell} \\ (SoC_k - SoC_{min}) \\ (SoC_{max} - SoC_{\mathrm{k}}) \end{bmatrix} \tag{3-12}$$

$$A_{eq} = [I - I \quad I - I - I \quad 0 \quad 0] \tag{3-13}$$

$$b_{eq} = \left[\left(P^l - \eta_k^{pv} P^{pv}\right)\right]' \tag{3-14}$$

$$lb = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad ub = \begin{bmatrix} P_{max}^{dis} \\ P_{max}^{ch} \\ P_{max}^{buy} \\ P_{max}^{sell} \\ P_{max}^{curtail} \\ 1 \\ 1 \end{bmatrix} \tag{3-15}$$

3.3 Model Predictive Controller Inputs

3.3.1 Solar Irradiance

For simplicity, the model of the solar panel itself is kept to a constant voltage supply, and a solar irradiance model is given to determine energy production on a minute-by-minute scale. This is done to ensure that solar irradiance time scale is at the same time scale as the simulation in order to use it for different controllers with accuracy. Data from the National Solar Radiation Database (NSRDB) [34] is sampled at 30-minute intervals and must be upsampled to the simulation sample rate from a site like the one in the simulator. The solar irradiance modeled in [32], used the Markov model to upsample the data from 48 points per day to 1440 points per day (30 minute to 1 minute). Stochastic variability is also added to the solar irradiance to mimic intermittent cloud cover that would be present in 1-minute data but is averaged out of 30-minute data. Since [2] uses the same site as the simulator in this thesis, the solar irradiance data was adapted from that. An average of 9-year data was used as a model for the solar irradiance input for the Model Predictive Controller.

3.3.2 Buy rates, sell rates and loads for MPC

Model Predictive Control in this thesis supports dynamic buy rates and sell rates. Since the site in the PSCG Simulator does not contain this information, data from Ameren, a utility

company in Illinois was used [34]. Ameren provides hourly prices of energy, which was used as the buy rate for the simulation. The sell rates were just obtained by multiplying buy rates by 0.95 to account for the possible friction costs.

Although this might not be accurate for the given site, it is a helpful tool to run the analysis. Once the Utility – scale PV + Storage facility owners have this information, they can use the tool to achieve accurate results. Last two sub-figures in Appendix B present a 5-day plot of the utility rates, while Appendix C has the yearly plots of the buy rates and sell rates.

Loads are provided in the database created in a one-minute resolution.

Autoregressive model technique and the Deep Learning toolbox in Matlab is used to forecast two days of buy rates, sell rates and loads as predicted inputs for MPC.

3.4 Cluster Computation

The current processing time of a yearly simulation with one-minute resolution is around 10hrs. For a study requiring combinations of 4 PV capacities, 16 battery profiles (4 battery power levels and 4 battery durations) MATLAB requires 10x65=650 hours, or 27 days. Not only is this a considerable processing time, but long running programs are remarkably difficult to debug.

Using MATLAB's compiler tool to implement the simulation as a license-free stand-alone executable, the simulation will be deployed to the cluster computer. The cluster computing allows the program to run around 200 tasks simultaneously which means the 27 days will be brought down to about 10 hours. And the license-free executable has the advantage of potential deployment to interested users. Figure 3-1 shows the architecture of cluster computers at UW-Milwaukee (UWM).

UWM's High Performance Computing Service provides powerful computational resources to UWM researchers and their student assistants. The current cluster, Mortimer, provides users with access to 116 compute nodes (Dell PowerEdge series), 2,724 total computing cores and 11,520 GiB (11.3 TiB) RAM [3].

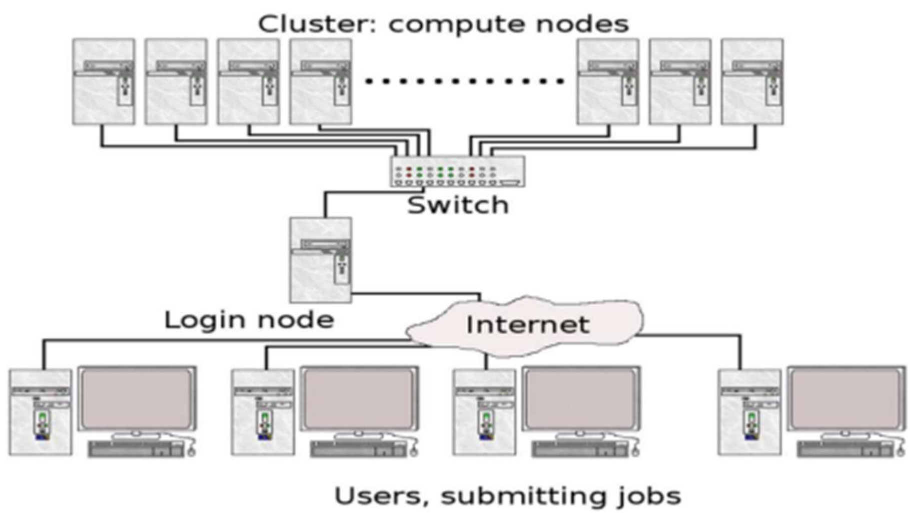

Figure 3-1: Cluster computers nodes architecture at University of Wisconsin-Milwaukee's cluster, Mortimer [3].

3.5 Results

3.5.1 MPC

The Model Predictive Controller is applied to the PSCG simulator based on section 3 and the results for the Grid Input Power[kW] and Battery Power[kW] are shown in Figure 3-2.

These results presented are for 5 days for a 4000kW PV Capacity, 2000kW Battery with a 4-hour battery duration. Additional plots, such as the solar irradiance, loads, buy rates, sell rates, and state of charge are included in Appendix C. These plots were useful to visually

validate that the MPC was commanding to charge during low buy rates and sell during high sell rates.

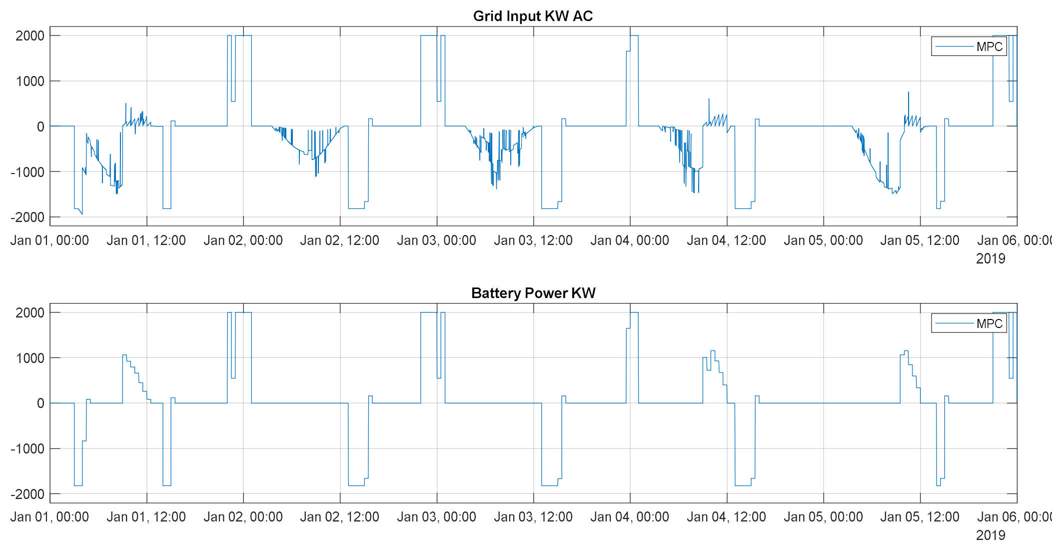

Figure 3-2: Grid Input and Battery Power plots for Model Predictive Controller for a facility with PV of 4000kW and a Battery power of 2000kW and Battery duration of 4 hours for 5 days of simulation.

3.5.2 Scheduled Battery Algorithm

Scheduled battery Input algorithm is a simple grid following scheduled control that typically charges during the day and discharges during the night, while maintaining the voltage constraints. The Battery Power input is shown in the second plot of Figure 3-3, while the Input power to the grid is shown in the first plot.

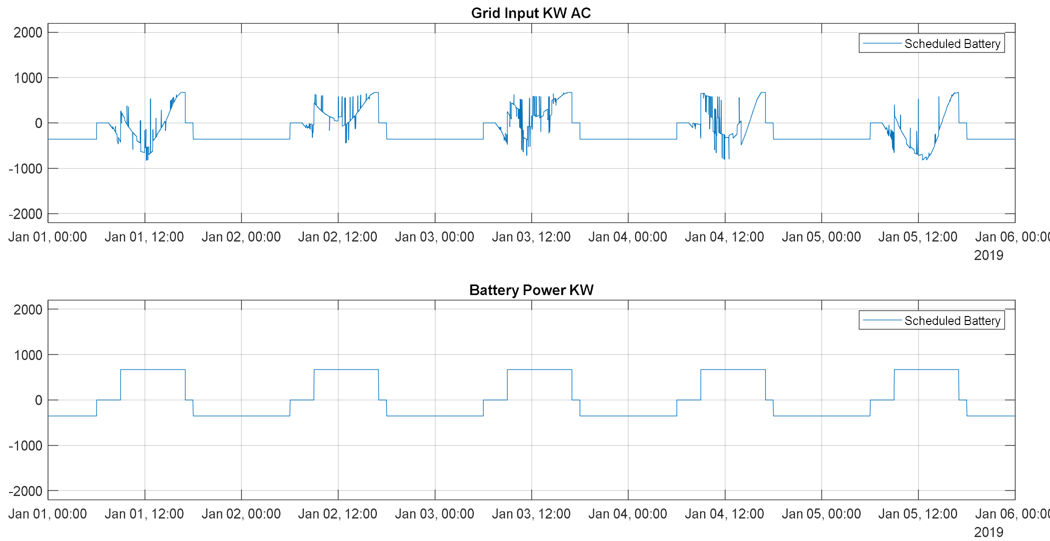

Figure 3-3: Grid Input and Battery Power plots for Scheduled battery controller for a facility with PV of 4000kW and a Battery power of 2000kW and Battery duration of 4 hours for 5 days of simulation.

For both the controller plots, if the Grid Input is positive, that means that the facility is buying power and if it is negative, it means the facility is selling power. In the battery power plots, a positive power indicates charging, while negative indicated discharging. Table 3-2 shows the profit made by both the controllers. MPC resulted in a significantly higher revenue than SBC

Control Method	**Revenue ($)**
Scheduled Battery Control	$ 337
Model Predictive Control	$ 580

Table 3-2: Cost comparison for a PV of 4000kW and a Battery power of 2000kW and Battery duration of 4 hours for 5 days of simulation.

3.6 Validation technique for optimal value in MILP

A validation tool was created to ensure that the MPC-MILP produces the optimal solution. This included rerunning the PSCG simulator for the MPC Results, where a slight change (charging/discharging) was made in the battery power at a certain MPC sample step, and the rest of the 5 days used the controller outputs provided by MPC. This was done while maintaining the constraints enforced by the PSCG Simulator. The cost that was caused by the change in charge/discharge power is referred as Validation cost in the following Figure 3-4. Figure 3-4 shows the plot where the battery power is attempted to decrease 100kW.

As predicted, the revenue made by the MPC without any changes presents the highest revenue. There are some intervals where the MPC cost and the Validation cost are equal, and this occurs mostly due to the constraints enforced by the PSCG Simulator. For example, at midnight on January 2nd, the Validation and MPC revenue are same since the state of charge was about to hit the minimum constraint with the existing discharge power, so the battery could not discharge anymore.

There are some cases where the increase in charging/discharging power did not cause any change in the revenue. Table 3-2 displays the revenues acquire for both these control strategies.

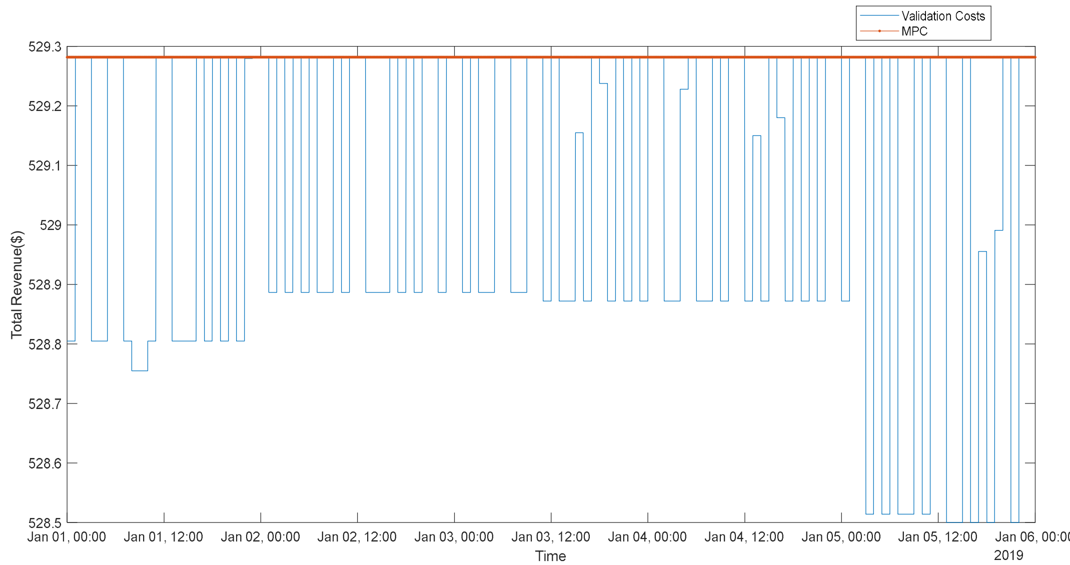

Figure 3-4 : Costs for the validation of the MPC Results where the discharge power was increased by 100kW for a 4000kW PV and 2000kW Battery with a duration of 4 hours.

3.7 Results Analysis

The following plots are results from an analysis of combination of PV size, battery capacity and battery duration. PV sizes of 1000kW, 2000kW, 3000kW, and 4000kW were tested. For each of these PV site a battery power range of $\frac{1}{4}, \frac{1}{2}$, 1 and 1.5 times the PV size was examined.

The results shown in Table 3-3 are the cases for each PV size with a certain selection process. The selection process included retrieving prices for all the combinations of battery power and battery duration mentioned above. For each PV size, only the case with the highest ROI is plotted to facilitate a clear visual representation of the results.

Table 3-3 shows the combination of battery power and duration for every PV size, where the highest ROI is achieved.

The same combination of PV, battery power and battery duration was used in Figures 3-5 through 3-12

Appendix A contains the tabulated results for all 64 cases for the Model Predictive Controller cases and the Scheduled Battery Controller.

PV (kW)	Battery Power(kW)	Battery Duration(hours)	ROI
1000	1500	1	0.1055
2000	3000	1	0.1307
3000	3000	1	0.1096
4000	4000	1	0.0955

Table 3-3: Values for each PV Power size for the maximum case of ROI.

3.7.1 Return on Investment

As mentioned previously, as the necessity for solar energy increases, it is necessary to encourage the commercial energy distributors to choose solar energy over fossil fuels. As observed in Figure 3-5, MPC has managed to increase the ROI almost by a factor of 2.

ROI was calculated for each facility using equation (3-16).

Total revenue is calculated based on the buying and selling rates at the grid. The investment is based on the PV and battery installed in the facility based on figures from [4] and [5] are shown in Table 3-4. In order to get an accurate set of results, it is suggested to use the pricing data at that site. As mentioned previously, these prices are just based on assumptions of buy rate and sell rate.

Cost	Price ($)
PV$\frac{\$}{kW}$	$883
Battery $\frac{\$}{kW}$	$50
Battery $\frac{\$}{kWh}$	$130

Table 3-4: PV and battery costs based on [2].

$$\frac{Total\ Revenue(\$)}{Investment(\$)} = \frac{Total\ Revenue}{(PV\ Size \cdot 883)+(Battery\ duration \cdot Battery\ power \cdot 130)+(Battery\ power \cdot 50)} \quad (3\text{-}16)$$

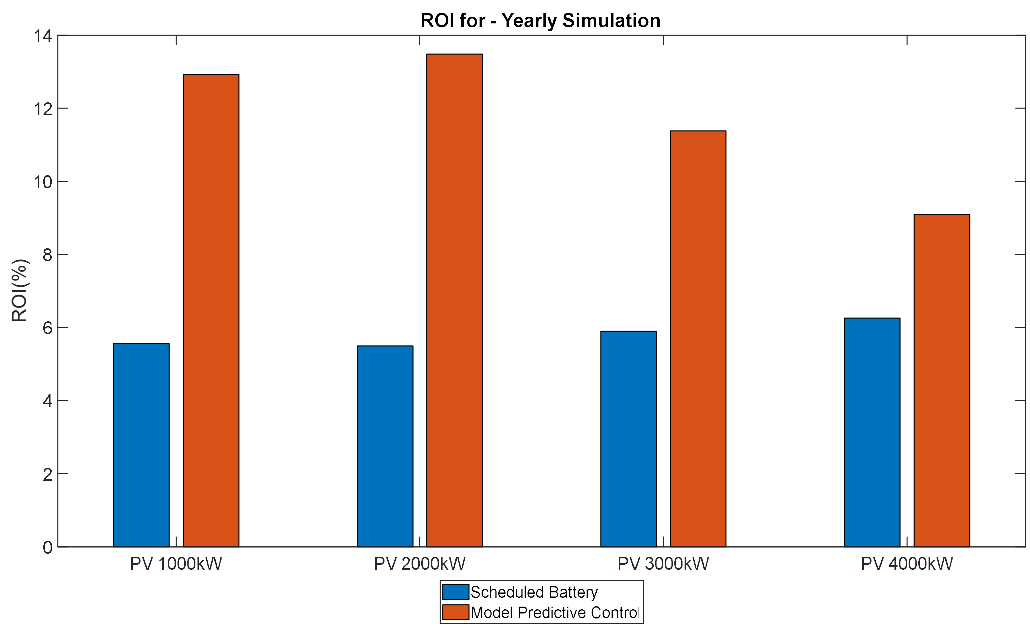

Figure 3-5: Comparison of Return on Investment (%) for a year based on the PV and battery configurations shown in Table 3-3.

3.7.2 Grid Power

In Figure 3-6, a negative net yield means the grid is selling more than buying. The comparison of net yield was interesting when compared to the ROI plots.

Although the MPC method amounted in selling fewer MWh, it was able to present a higher ROI since MPC was able to predict respond to price variations in energy. Figure 3-7 and Figure 3-8 show the amount of energy bought and energy sold over a year, respectively. Although MPC bought a larger amount of energy, it is still generating more revenue that scheduled battery.

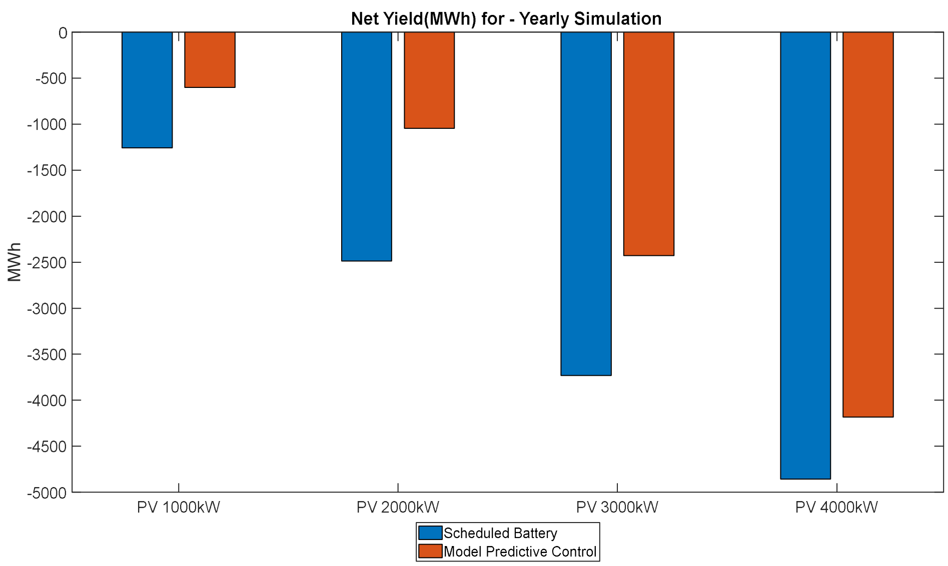

Figure 3-6: Comparison of Net Yield (MWh) for a year based on the PV and battery configurations shown in Table 3-3

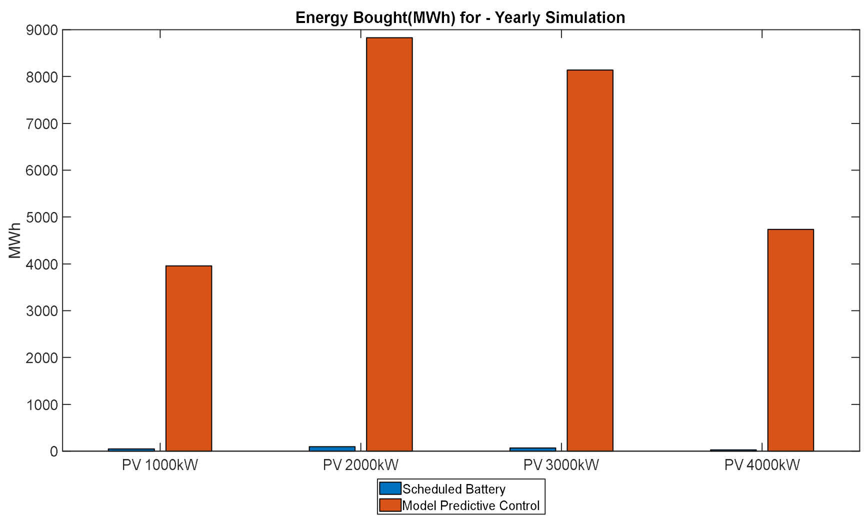

Figure 3-7 : Comparison of Total Energy Bought (MWh) for a year based on the PV and battery configurations shown in Table 3-3.

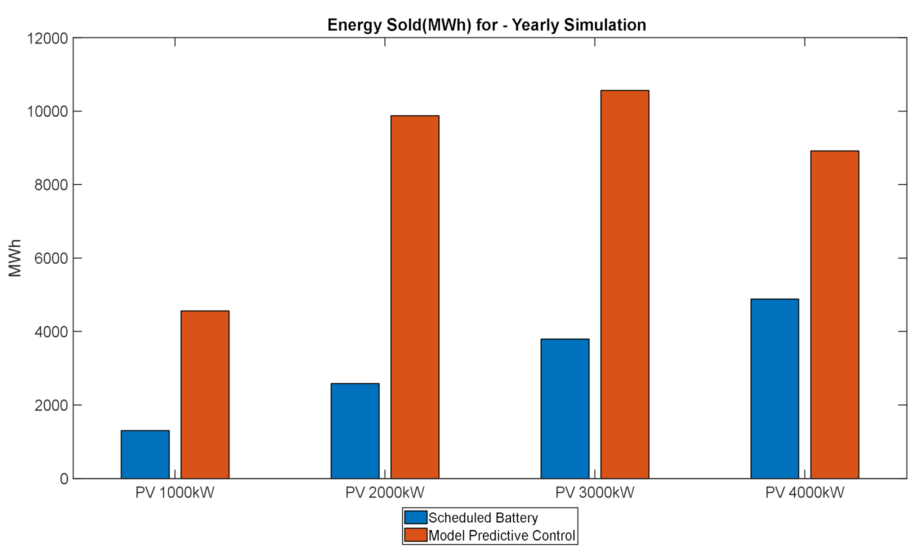

Figure 3-8: Comparison of Total Energy Sold (MWh) for a year based on the PV and battery configurations shown in Table 3-3.

3.7.3 Line Losses

Line losses are calculated as a comparison to the case when both PV size and battery are 0kW. Figure 3-9 shows that there is a significant increase in the line losses for the Model Predictive Control. This is believed to be due to MPC's ability to switch from charging to discharging every in response to price variations.

The second plot in Figure 3-2 and Figure 3-3 show the battery behavior in the Model Predictive Controller and Scheduled Battery Controller. Although MPC considers the charging and discharging efficiencies of the battery and the efficiency of the grid, the decision to switch frequently is because the cost function is based on just the total revenue and doesn't see the affect that this pattern can have in the long run.

As seen in Figure 3-5, the return on investment of Model Predictive Controller is higher than the Scheduled Battery Control even though the line losses are higher.

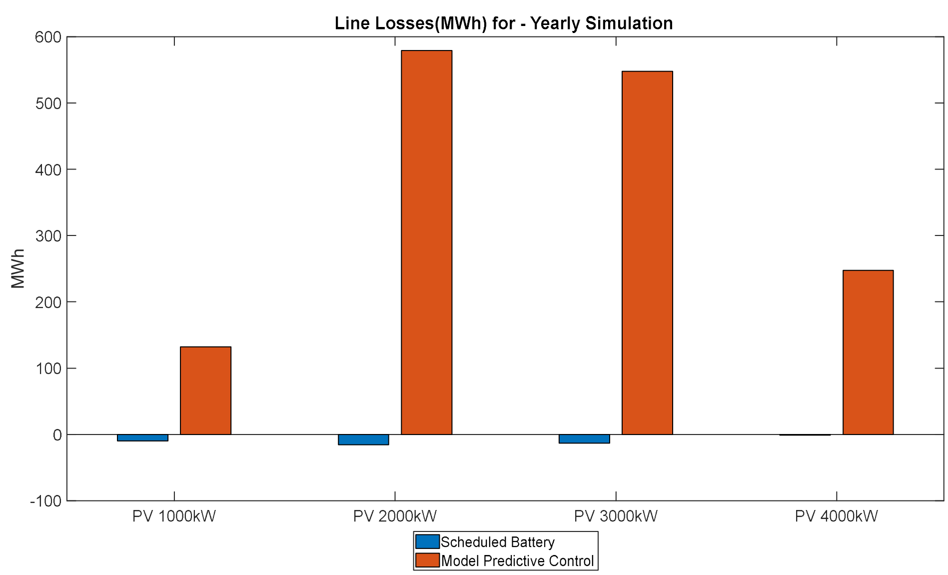

Figure 3-9: Comparison of Line Losses (MWh) for a year based on the PV and battery configurations shown in Table 3-3.

3.7.4 Battery power

The effects of higher charging and discharging can be seen in the line losses data. However, energy storage system in a PV facility is very useful to mitigate curtailment, since additional PV during high PV generation times is sent to the battery. As observed in Figure 3-12, the curtailment is significantly lower in the Model Predictive Controller cases.

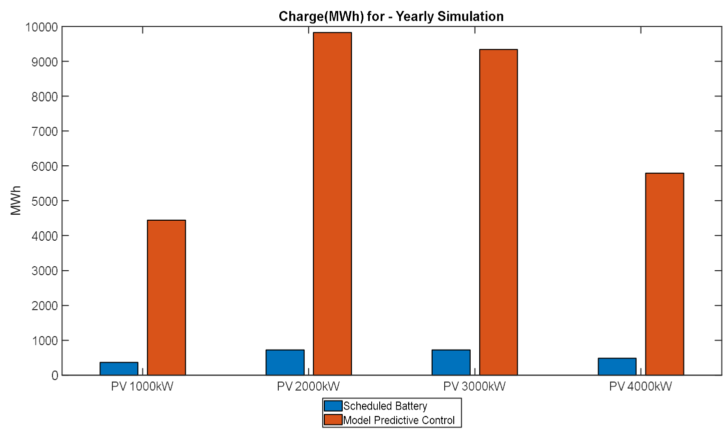

Figure 3-10 : Comparison of total charge (MWh) for a year based on the PV and battery configurations shown in Table 3-3

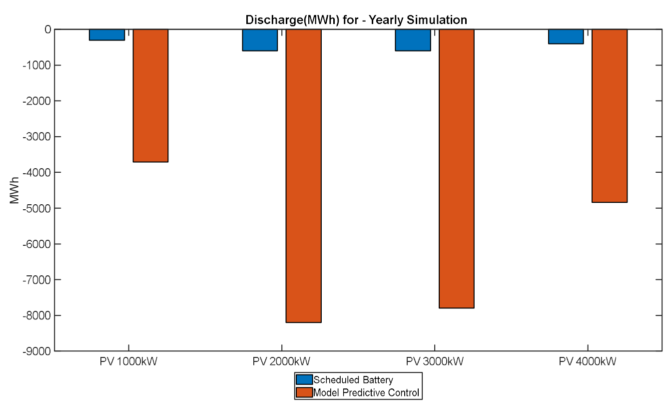

Figure 3-11: Comparison of total discharge (MWh) for a year based on the PV and battery configurations shown in Table 3-3.

3.7.5 Curtailment

The curtailment in the Model Predictive Control is caused by the change of PV within that sample time step. For example, if the PV predicted for the next half hour is lower than the actual PV from the simulator, MPC will set the controlled values of P^{ch} or P^{dis} to a low value and the "connection-point' voltage limit may be reached, leading to curtailment.

The curtailment cause by the scheduled battery is still higher than that of the MPC since the Schedule Based Control has no element of dynamic response.

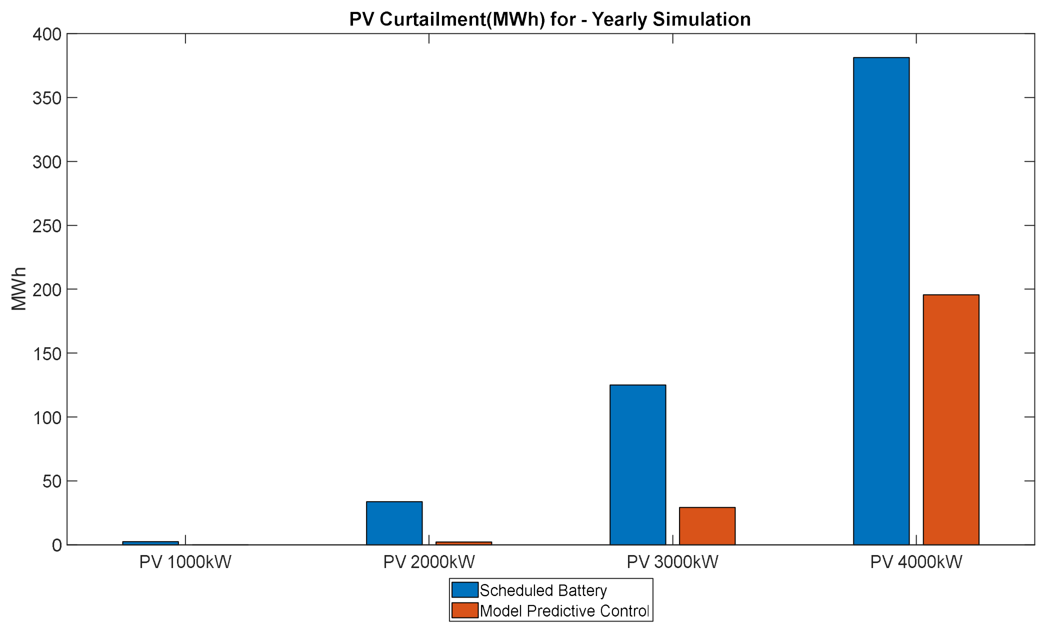

Figure 3-12 : Comparison of curtailment (MWh) for a year based on the PV and battery configurations shown in Table 3-3.

4 Conclusion

Improvements in PV technologies over the last decade have brought about notable increases in their ROI. PV technologies currently have one of the lowest ROI, when compared to fossil fuels and a few renewable energy sources. Cost optimization methods such as implementing Model Predictive Control can increase the ROI while maintaining the grid and battery constraints and considering their efficiencies. A higher ROI encourages the commercial energy distribution to steer towards solar energy.

A comparison of the results to the Scheduled Battery Controller shows that the Model Predictive Controller can achieve a higher ROI. The line losses are higher, since the controller tries buy the energy only when buy rates are lower and sells most of the energy when sell rates are higher.

The goal of the thesis was to introduce Model Predictive Control to a utility-scale PV + Storage facility, and it was achieved with positive results. This tool can be applied to different sites to measure analyze the possibility of implementing a model predictive controller.

5 Future Work

5.1 Battery life and Line Losses

Currently the line losses in the MPC case are significantly higher than that of the scheduled battery. This is caused by the freedom to charge and discharge at each sample timestep (30 minutes in the PSCG Simulator).

The frequent change between charge and discharge can also lead to a shorter battery life.

A modified cost function in MPC can be explored which penalizes the cost of the system as the frequency of the switch between charging and discharging decision variables increases.

5.2 Grid Limit Prediction (based on Load, Utility and PV predictions in the MPC)

The grid limit in the PSCG Simulator is dynamic. However, this was not accounted for in the MPC formulation. MPC would require a prediction of the grid, and P_{max}^{sell} will be an input vector, similar to the buy and sell rates, instead of a constant.

In this thesis, the tool that has been implemented in the PSCG Simulator to a Model Predictive Controller, has a potential to be used to mitigate the concerns addressed in this section.

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7 Appendix A : Additional Information for 65 cases

Table 7-1, Table 7-2, Table 7-3 contain results produced by Model Predictive Control for all 65 cases evaluated in section 3.7. Table 7-4, Table 7-5, Table 7-6 contain results produced by Schedule based control for all 65 cases evaluated in section 3.7

- Revenue- calculation based on the sell and buy rates and the and the Input power to the grid.
- Investment- calculation based on the Table 3-4 and the size of the PV and Battery system.
- Return on Investment is $\frac{Revenue}{Investment}$.
- Line Losses (MWh) is the cumulative line loss that has occurred over the year (MWh).
- Curtailment (MWh) is the cumulative curtailment that has occurred over the year.
- Peak Voltage(V) is the max voltage that has occurred in the year.
- Net Yield (MWh) is the cumulative power of the power that is transferred to the grid over the year.
- Energy Bought (MWh) is the cumulative power that is bought into the grid over the year (MWh).
- Energy Sold (MWh) is the cumulative power that is sold from the grid over the year (MWh).
- Charging Energy (MWh) is the cumulative power that is used for charging the battery over the year.
- Discharging Energy (MWh) is the cumulative power that is used for discharging the battery over the year.

Model Predictive Control Results

PV Max(kW)	Bat Max(kW)	Bat_Dur(hours)	Revenue($)	Investment($)	ROI(%)	Highest MPC ROI
0	0	0	0	0	0.00	
1000	250	1	77023	928000	0.00	
1000	250	2	72863	960500	0.00	
1000	250	4	73756	1025500	0.00	
1000	250	8	72826	1155500	0.00	
1000	500	1	82882	973000	0.00	
1000	500	2	86791	1038000	0.00	
1000	500	4	85206	1168000	0.00	
1000	500	8	82882	1428000	0.00	
1000	1000	1	109622	1063000	0.00	
1000	1000	2	113037	1193000	0.00	
1000	1000	4	107127	1453000	0.00	
1000	1000	8	110233	1973000	0.00	
1000	**1500**	**1**	**149040**	**1153000**	**0.00**	**x**
1000	1500	2	140350	1348000	0.00	
1000	1500	4	142305	1738000	0.00	
1000	1500	8	144080	2518000	0.00	
2000	500	1	147163	1856000	0.00	
2000	500	2	151358	1921000	0.00	
2000	500	4	149235	2051000	0.00	
2000	500	8	145768	2311000	0.00	
2000	1000	1	170566	1946000	0.00	
2000	1000	2	172672	2076000	0.00	
2000	1000	4	168054	2336000	0.00	
2000	1000	8	172198	2856000	0.00	
2000	2000	1	240265	2126000	0.00	
2000	2000	2	227124	2386000	0.00	
2000	2000	4	229151	2906000	0.00	
2000	2000	8	232264	3946000	0.00	
2000	**3000**	**1**	**310983**	**2306000**	**0.00**	**x**
2000	3000	2	305652	2696000	0.00	
2000	3000	4	311423	3476000	0.00	
2000	3000	8	321106	5036000	0.00	
3000	750	1	217455	2784000	0.00	
3000	750	2	218103	2881500	0.00	
3000	750	4	219071	3076500	0.00	
3000	750	8	218996	3466500	0.00	
3000	1500	1	263784	2919000	0.00	
3000	1500	2	257469	3114000	0.00	
3000	1500	4	261523	3504000	0.00	
3000	1500	8	263186	4284000	0.00	
3000	3000	1	362855	3189000	0.00	**x**
3000	3000	2	359143	3579000	0.00	
3000	3000	4	364149	4359000	0.00	
3000	3000	8	371221	5919000	0.00	
3000	4500	1	309612	3459000	0.00	
3000	4500	2	332166	4044000	0.00	
3000	4500	4	355070	5214000	0.00	
3000	4500	8	365037	7554000	0.00	
4000	1000	1	289385	3712000	0.00	
4000	1000	2	291555	3842000	0.00	
4000	1000	4	290842	4102000	0.00	
4000	1000	8	294602	4622000	0.00	
4000	2000	1	353965	3892000	0.00	
4000	2000	2	342565	4152000	0.00	
4000	2000	4	351157	4672000	0.00	
4000	2000	8	349623	5712000	0.00	
4000	4000	1	374031	4252000	0.00	**x**
4000	4000	2	388947	4772000	0.00	
4000	4000	4	404444	5812000	0.00	
4000	4000	8	405452	7892000	0.00	
4000	6000	1	400485	4612000	0.00	
4000	6000	2	403874	5392000	0.00	
4000	6000	4	416836	6952000	0.00	
4000	6000	8	427535	10072000	0.00	

Table 7-1 : Return on Investment Results for Model Predictive Control.

Model Predictive Control Results

PV Max(kW)	Bat Max(kW)	Bat_Dur(hours)	Net Yield	Net Energy Bought(MWh)	Net Energy Sold(MWh)	Net Energy Charge(MWh)	Net Energy Discharged(MWh)	Highest MPC ROI
0	0	0	0	0	0	0	0	
1000	250	1	-1248	469	-1716	520	-435	
1000	250	2	-1280	283	-1563	325	-272	
1000	250	4	-1265	338	-1602	421	-351	
1000	250	8	-1257	320	-1576	469	-392	
1000	500	1	-1181	773	-1954	926	-773	
1000	500	2	-1156	932	-2089	1076	-899	
1000	500	4	-1163	876	-2039	1037	-866	
1000	500	8	-1125	887	-2012	1271	-1063	
1000	1000	1	-928	2087	-3015	2457	-2051	
1000	1000	2	-896	2251	-3147	2655	-2217	
1000	1000	4	-926	2041	-2967	2474	-2066	
1000	1000	8	-899	2189	-3088	2648	-2213	
1000	**1500**	**1**	**-601**	**3958**	**-4558**	**4442**	**-3709**	**x**
1000	1500	2	-660	3583	-4244	4082	-3409	
1000	1500	4	-639	3698	-4337	4215	-3521	
1000	1500	8	-652	3716	-4368	4146	-3465	
2000	500	1	-2518	682	-3200	847	-707	
2000	500	2	-2492	851	-3343	995	-831	
2000	500	4	-2491	792	-3283	1002	-837	
2000	500	8	-2443	769	-3212	1332	-1113	
2000	1000	1	-2278	1840	-4118	2322	-1939	
2000	1000	2	-2242	1974	-4216	2528	-2111	
2000	1000	4	-2250	1833	-4084	2492	-2081	
2000	1000	8	-2205	2040	-4245	2789	-2330	
2000	2000	1	-1633	5293	-6925	6246	-5215	
2000	2000	2	-1724	4724	-6448	5686	-4748	
2000	2000	4	-1731	4777	-6508	5663	-4730	
2000	2000	8	-1732	4853	-6586	5672	-4740	
2000	**3000**	**1**	**-1044**	**8831**	**-9875**	**9823**	**-8201**	**x**
2000	3000	2	-1096	8538	-9634	9509	-7940	
2000	3000	4	-1093	8675	-9768	9520	-7949	
2000	3000	8	-1053	9010	-10064	9798	-8187	
3000	750	1	-3693	1055	-4747	1402	-1170	
3000	750	2	-3672	1116	-4788	1551	-1295	
3000	750	4	-3639	1213	-4853	1815	-1516	
3000	750	8	-3607	1255	-4862	2133	-1782	
3000	1500	1	-3267	3262	-6529	4081	-3407	
3000	1500	2	-3305	3022	-6328	3935	-3286	
3000	1500	4	-3278	3197	-6475	4164	-3478	
3000	1500	8	-3274	3257	-6532	4237	-3541	
3000	**3000**	**1**	**-2430**	**8137**	**-10567**	**9342**	**-7800**	**x**
3000	3000	2	-2468	7946	-10414	9119	-7615	
3000	3000	4	-2483	8026	-10509	9003	-7519	
3000	3000	8	-2460	8256	-10715	9143	-7640	
3000	4500	1	-2887	5615	-8502	6442	-5379	
3000	4500	2	-2732	6611	-9343	7427	-6203	
3000	4500	4	-2540	7716	-10256	8632	-7211	
3000	4500	8	-2430	8253	-10682	9336	-7804	
4000	1000	1	-4714	1719	-6433	2283	-1906	
4000	1000	2	-4699	1820	-6518	2493	-2082	
4000	1000	4	-4714	1789	-6503	2638	-2203	
4000	1000	8	-4711	1903	-6614	2894	-2418	
4000	2000	1	-4183	4735	-8918	5793	-4837	
4000	2000	2	-4296	4203	-8499	5310	-4434	
4000	2000	4	-4263	4504	-8767	5503	-4597	
4000	2000	8	-4285	4443	-8728	5449	-4554	
4000	**4000**	**1**	**-4039**	**5781**	**-9821**	**6730**	**-5620**	**x**
4000	4000	2	-3939	6400	-10339	7321	-6114	
4000	4000	4	-3798	7141	-10939	8153	-6811	
4000	4000	8	-3768	7329	-11098	8537	-7136	
4000	6000	1	-3843	6975	-10818	7918	-6612	
4000	6000	2	-3821	7132	-10953	8076	-6746	
4000	6000	4	-3679	7876	-11556	9046	-7559	
4000	6000	8	-3607	8291	-11898	9566	-7999	

Table 7-2: PSCG Results for various Energies produced by Model Predictive Control.

Model Predictive Control Results								
PV Max(kW)	Bat Max(kW)	Bat_Dur (hours)	Line Losses(MWh)	Curtailment (MWh)	Peak Voltage(V)	Percent Loading	Net LTC	Highest ROI
0	0	0	316	0	126	0	256841	
1000	250	1	-7	0	127	14	-26212	
1000	250	2	-10	0	127	13	-44368	
1000	250	4	-9	0	127	14	-38204	
1000	250	8	-9	0	127	14	-39018	
1000	500	1	-3	0	127	17	-94765	
1000	500	2	0	0	127	17	-101832	
1000	500	4	-1	0	127	17	-100498	
1000	500	8	0	0	127	17	-99371	
1000	1000	1	50	0	128	23	-136367	
1000	1000	2	55	0	128	23	-142080	
1000	1000	4	50	0	128	23	-132721	
1000	1000	8	55	0	128	23	-136744	
1000	**1500**	**1**	**132**	**0**	**128**	**28**	**-106926**	**x**
1000	1500	2	119	0	128	28	-101871	
1000	1500	4	126	0	128	28	-100853	
1000	1500	8	128	0	128	28	-98063	
2000	500	1	-7	10	128	28	-114515	
2000	500	2	-4	12	128	29	-122356	
2000	500	4	-5	12	128	29	-118527	
2000	500	8	-5	6	128	29	-116972	
2000	1000	1	43	7	129	34	-154924	
2000	1000	2	48	8	129	35	-157940	
2000	1000	4	45	6	129	34	-150130	
2000	1000	8	53	4	129	34	-160476	
2000	2000	1	244	4	130	45	-99574	
2000	2000	2	218	6	130	45	-98091	
2000	2000	4	227	3	130	45	-94663	
2000	2000	8	234	3	130	45	-91748	
2000	**3000**	**1**	**579**	**2**	**130**	**50**	**-69983**	**x**
2000	3000	2	559	3	130	51	-66810	
2000	3000	4	576	3	130	48	-65310	
2000	3000	8	609	3	130	50	-62492	
3000	750	1	20	77	129	44	-137371	
3000	750	2	22	74	129	43	-136954	
3000	750	4	26	63	129	43	-142519	
3000	750	8	26	44	129	43	-141754	
3000	1500	1	123	60	130	50	-143242	
3000	1500	2	120	47	130	49	-139727	
3000	1500	4	132	37	130	50	-139048	
3000	1500	8	138	30	130	50	-137842	
3000	**3000**	**1**	**548**	**29**	**130**	**53**	**-92160**	**x**
3000	3000	2	535	29	130	53	-91297	
3000	3000	4	549	35	130	63	-87285	
3000	3000	8	571	38	130	56	-84455	
3000	4500	1	395	52	133	84	-91473	
3000	4500	2	470	45	133	83	-86997	
3000	4500	4	560	41	131	76	-85420	
3000	4500	8	610	40	131	78	-83546	
4000	1000	1	67	244	130	56	-190611	
4000	1000	2	72	225	130	56	-191939	
4000	1000	4	75	186	131	56	-189514	
4000	1000	8	79	148	130	56	-195405	
4000	2000	1	247	196	130	59	-137489	
4000	2000	2	227	163	131	61	-131597	
4000	2000	4	249	165	131	65	-130510	
4000	2000	8	250	155	130	62	-128088	
4000	**4000**	**1**	**416**	**185**	**130**	**67**	**-110762**	**x**
4000	4000	2	468	189	132	82	-108019	
4000	4000	4	527	195	132	75	-103771	
4000	4000	8	557	166	131	83	-103410	
4000	6000	1	509	186	135	98	-106385	
4000	6000	2	535	183	134	100	-104408	
4000	6000	4	600	168	132	94	-100030	
4000	6000	8	637	162	134	111	-101310	

Table 7-3 : PSCG Results produced by Model Predictive Control.

Scheduled Battery Results

PV Max(kW)	Bat Max(kW)	Bat_Dur(hours)	Revenue($)	Investment($)	ROI(%)	Highest MPC ROI
0	0	0	0	0	0.00	
1000	250	1	65925	928000	0.00	
1000	250	2	65455	960500	0.00	
1000	250	4	64665	1025500	0.00	
1000	250	8	63614	1155500	0.00	
1000	500	1	65455	973000	0.00	
1000	500	2	64665	1038000	0.00	
1000	500	4	63614	1168000	0.00	
1000	500	8	63584	1428000	0.00	
1000	1000	1	64665	1063000	0.00	
1000	1000	2	63614	1193000	0.00	
1000	1000	4	63584	1453000	0.00	
1000	1000	8	70308	1973000	0.00	
1000	**1500**	**1**	**64054**	**1153000**	**0.00**	**x**
1000	1500	2	63268	1348000	0.00	
1000	1500	4	66008	1738000	0.00	
1000	1500	8	82729	2518000	0.00	
2000	500	1	129635	1856000	0.00	
2000	500	2	128873	1921000	0.00	
2000	500	4	127613	2051000	0.00	
2000	500	8	126054	2311000	0.00	
2000	1000	1	128873	1946000	0.00	
2000	1000	2	127613	2076000	0.00	
2000	1000	4	126054	2336000	0.00	
2000	1000	8	126647	2856000	0.00	
2000	2000	1	127613	2126000	0.00	
2000	2000	2	126054	2386000	0.00	
2000	2000	4	126647	2906000	0.00	
2000	2000	8	140060	3946000	0.00	
2000	**3000**	**1**	**126677**	**2306000**	**0.00**	**x**
2000	3000	2	125763	2696000	0.00	
2000	3000	4	131632	3476000	0.00	
2000	3000	8	164077	5036000	0.00	
3000	750	1	190448	2784000	0.00	
3000	750	2	189602	2881500	0.00	
3000	750	4	188208	3076500	0.00	
3000	750	8	186584	3466500	0.00	
3000	1500	1	189602	2919000	0.00	
3000	1500	2	188208	3114000	0.00	
3000	1500	4	186584	3504000	0.00	
3000	1500	8	188373	4284000	0.00	
3000	**3000**	**1**	**188208**	**3189000**	**0.00**	**x**
3000	3000	2	186584	3579000	0.00	
3000	3000	4	188373	4359000	0.00	
3000	3000	8	208730	5919000	0.00	
3000	4500	1	187201	3459000	0.00	
3000	4500	2	186648	4044000	0.00	
3000	4500	4	196277	5214000	0.00	
3000	4500	8	244304	7554000	0.00	
4000	1000	1	243504	3712000	0.00	
4000	1000	2	243505	3842000	0.00	
4000	1000	4	243676	4102000	0.00	
4000	1000	8	244457	4622000	0.00	
4000	2000	1	243505	3892000	0.00	
4000	2000	2	243676	4152000	0.00	
4000	2000	4	244457	4672000	0.00	
4000	2000	8	248926	5712000	0.00	
4000	**4000**	**1**	**243676**	**4252000**	**0.00**	**x**
4000	4000	2	244457	4772000	0.00	
4000	4000	4	248926	5812000	0.00	
4000	4000	8	276890	7892000	0.00	
4000	6000	1	244006	4612000	0.00	
4000	6000	2	246045	5392000	0.00	
4000	6000	4	259967	6952000	0.00	
4000	6000	8	322400	10072000	0.00	

Table 7-4 : Return on Investment Results for Schedule Based Control.

Scheduled Battery Results

Bat Max(kW)	Bat_Dur(hours)	Net Yield	Energy Bought(MWh)	Energy Sold(MWh)	Energy Charge(MWh)	Energy Discharged(MWh)	Highest MPC ROI
0	0	0	0	0	0	0	
250	1	-1317	2	-1320	60	-50	
250	2	-1306	7	-1313	120	-100	
250	4	-1282	23	-1305	241	-201	
250	8	-1234	77	-1311	481	-402	
500	1	-1306	7	-1313	120	-100	
500	2	-1282	23	-1305	241	-201	
500	4	-1234	77	-1311	481	-402	
500	8	-1138	270	-1409	962	-803	
1000	1	-1282	23	-1305	241	-201	
1000	2	-1234	77	-1311	481	-402	
1000	4	-1138	270	-1409	962	-803	
1000	8	-944	936	-1880	1924	-1606	
1500	**1**	**-1258**	**46**	**-1304**	**361**	**-301**	**x**
1500	2	-1186	160	-1346	721	-602	
1500	4	-1041	565	-1606	1443	-1205	
1500	8	-750	1849	-2599	2883	-2407	
500	1	-2591	4	-2595	120	-100	
500	2	-2571	14	-2584	241	-201	
500	4	-2530	46	-2575	481	-402	
500	8	-2445	153	-2599	962	-803	
1000	1	-2571	14	-2584	241	-201	
1000	2	-2530	46	-2575	481	-402	
1000	4	-2445	153	-2599	962	-803	
1000	8	-2266	541	-2807	1924	-1606	
2000	1	-2530	46	-2575	481	-402	
2000	2	-2445	153	-2599	962	-803	
2000	4	-2266	541	-2807	1924	-1606	
2000	8	-1882	1862	-3745	3838	-3204	
3000	**1**	**-2488**	**92**	**-2580**	**721**	**-602**	**x**
3000	2	-2357	320	-2677	1443	-1205	
3000	4	-2077	1126	-3203	2883	-2407	
3000	8	-1496	3654	-5149	5721	-4776	
750	1	-3806	6	-3812	180	-151	
750	2	-3782	21	-3802	361	-301	
750	4	-3730	68	-3799	721	-602	
750	8	-3618	230	-3848	1443	-1205	
1500	1	-3782	21	-3802	361	-301	
1500	2	-3730	68	-3799	721	-602	
1500	4	-3618	230	-3848	1443	-1205	
1500	8	-3368	810	-4178	2883	-2407	
3000	**1**	**-3730**	**68**	**-3799**	**721**	**-602**	**x**
3000	2	-3618	230	-3848	1443	-1205	
3000	4	-3368	810	-4178	2883	-2407	
3000	8	-2810	2766	-5576	5721	-4776	
4500	1	-3675	139	-3814	1082	-903	
4500	2	-3496	480	-3976	2164	-1806	
4500	4	-3096	1682	-4778	4312	-3600	
4500	8	-2242	5401	-7643	8483	-7082	
1000	1	-4866	9	-4874	241	-201	
1000	2	-4856	28	-4884	481	-402	
1000	4	-4828	91	-4919	962	-803	
1000	8	-4738	307	-5044	1924	-1606	
2000	1	-4856	28	-4884	481	-402	
2000	2	-4828	91	-4919	962	-803	
2000	4	-4738	307	-5044	1924	-1606	
2000	8	-4448	1077	-5525	3838	-3204	
4000	**1**	**-4828**	**91**	**-4919**	**962**	**-803**	**x**
4000	2	-4738	307	-5044	1924	-1606	
4000	4	-4448	1077	-5525	3838	-3204	
4000	8	-3733	3657	-7390	7569	-6318	
6000	1	-4789	185	-4974	1443	-1205	
6000	2	-4606	639	-5245	2883	-2407	
6000	4	-4100	2229	-6329	5721	-4776	
6000	8	-2974	7090	-10064	11161	-9317	

Table 7-5 : PSCG Results for various Energies produced by Schedule Based Control.

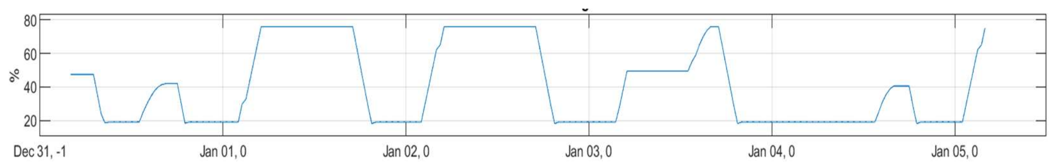
Schedule batttery Control Results

PV Max(kW)	Bat Max(kW)	Bat_Dur(hours)	Line Losses(MWh)	Curtailment(MWh)	Peak Voltage(V)	Percent Loading	Net LTC	Highest ROI
0	0	0	324.1	0	126	0	68347	
1000	250	1	-11.6	4	126	12	-19657	
1000	250	2	-11.3	4	126	11	-17815	
1000	250	4	-10.5	3	126	11	-13980	
1000	250	8	-8.5	2	126	10	-6317	
1000	500	1	-11.3	4	126	11	-17815	
1000	500	2	-10.5	3	126	11	-13980	
1000	500	4	-8.5	2	126	10	-6317	
1000	500	8	-2.3	1	126	9	8543	
1000	1000	1	-10.5	3	126	11	-13980	
1000	1000	2	-8.5	2	126	10	-6317	
1000	1000	4	-2.3	1	126	9	8543	
1000	1000	8	17.5	0	126	9	40345	
1000	**1500**	**1**	**-9.6**	**3**	**126**	**10**	**-9826**	**x**
1000	1500	2	-5.6	1	126	9	1245	
1000	1500	4	6.5	0	126	9	22041	
1000	1500	8	43.6	1	126	12	49283	
2000	500	1	-16.8	53	126	23	-28614	
2000	500	2	-16.9	48	126	23	-25221	
2000	500	4	-16.5	40	126	22	-18525	
2000	500	8	-14.4	28	126	19	-4675	
2000	1000	1	-16.9	48	126	23	-25221	
2000	1000	2	-16.5	40	126	22	-18525	
2000	1000	4	-14.4	28	126	19	-4675	
2000	1000	8	-3.5	12	126	19	23407	
2000	2000	1	-16.5	40	126	22	-18525	
2000	2000	2	-14.4	28	126	19	-4675	
2000	2000	4	-3.5	12	126	19	23407	
2000	2000	8	36.7	9	126	19	55374	
2000	**3000**	**1**	**-15.7**	**34**	**126**	**21**	**-11726**	**x**
2000	3000	2	-10.0	18	126	19	8586	
2000	3000	4	14.8	8	126	19	27868	
2000	3000	8	115.5	15	126	27	133030	
3000	750	1	-10.8	159	126	34	-34293	
3000	750	2	-12.0	147	126	34	-29415	
3000	750	4	-13.4	125	126	32	-18901	
3000	750	8	-13.0	91	126	29	1757	
3000	1500	1	-12.0	147	126	34	-29415	
3000	1500	2	-13.4	125	126	32	-18901	
3000	1500	4	-13.0	91	126	29	1757	
3000	1500	8	0.5	50	126	28	14688	
3000	**3000**	**1**	**-13.4**	**125**	**126**	**32**	**-18901**	**x**
3000	3000	2	-13.0	91	126	29	1757	
3000	3000	4	0.5	50	126	28	14688	
3000	3000	8	77.1	34	126	29	105940	
3000	4500	1	-13.7	107	126	31	-8652	
3000	4500	2	-7.8	67	126	28	19950	
3000	4500	4	26.3	33	126	28	57392	
3000	4500	8	266.0	43	126	44	138247	
4000	1000	1	1.0	420	126	45	-43316	
4000	1000	2	-0.9	381	126	44	-36997	
4000	1000	4	-3.8	312	126	42	-24347	
4000	1000	8	-5.0	208	126	38	3343	
4000	2000	1	-0.9	381	126	44	-36997	
4000	2000	2	-3.8	312	126	42	-24347	
4000	2000	4	-5.0	208	126	38	3343	
4000	2000	8	6.7	111	126	37	29035	
4000	**4000**	**1**	**-3.8**	**312**	**126**	**42**	**-24347**	**x**
4000	4000	2	-5.0	208	126	38	3343	
4000	4000	4	6.7	111	126	37	29035	
4000	4000	8	156.6	71	126	42	90736	
4000	6000	1	-5.2	254	126	40	-10616	
4000	6000	2	-0.6	146	126	37	4066	
4000	6000	4	53.7	78	126	37	88012	
4000	6000	8	456.9	103	126	53	125290	

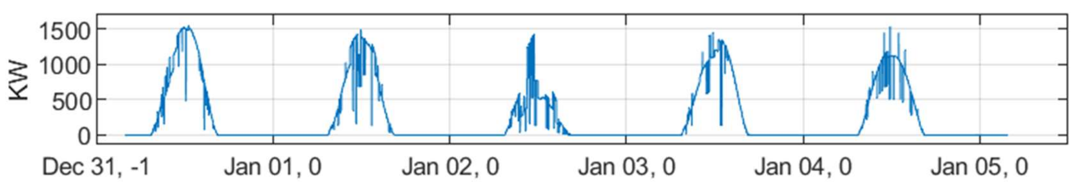
Table 7-6: PSCG Results produced by Schedule Based Control.

8 Appendix B: Solar irradiance, loads, buy rates, and sell rates input plots and state of charge plot for Model Predictive Controller of 5-day analysis.

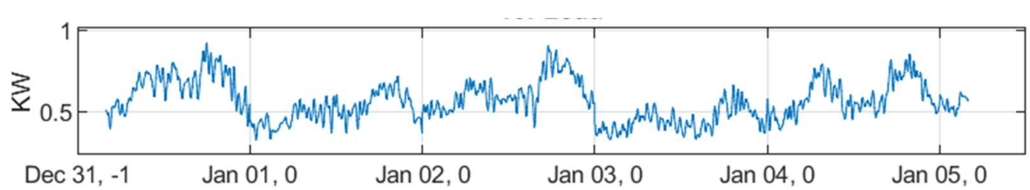
State of Charge (%)



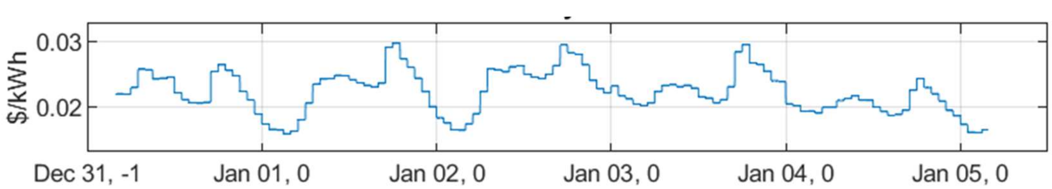
Photovoltaic Power(kW)



Load(kW)



Buy Rates($/kWh)



Sell Rate($/kWh)

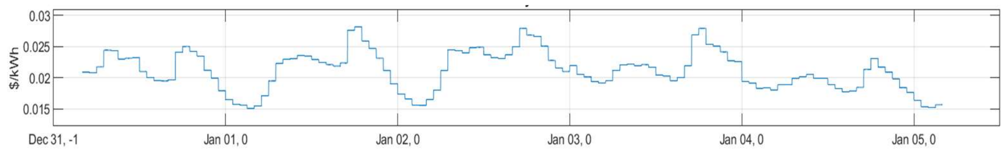


Figure 8-1: Plots for Model Predictive Controller simulation with PV at 4000kW, Battery at 2000kW and battery duration at 4 hours.

9 Appendix C: Buy rates and sell rates data from an Ameren.

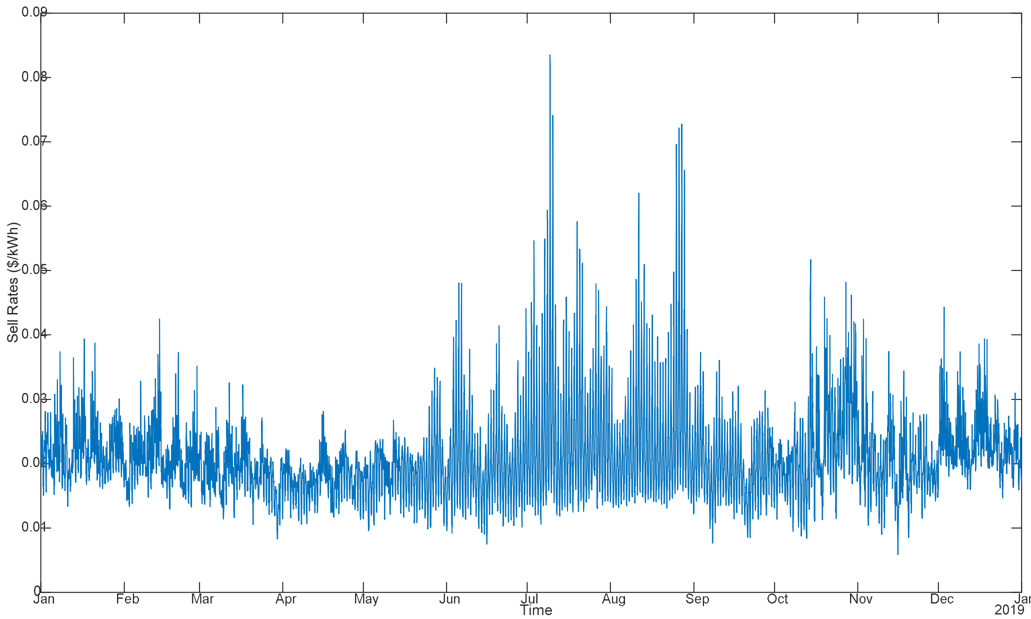


Figure 9-1 : Sell rates for one year of simulation base, which is 0.95 of the buy rates from an Illinois utility company, Ameren [34].

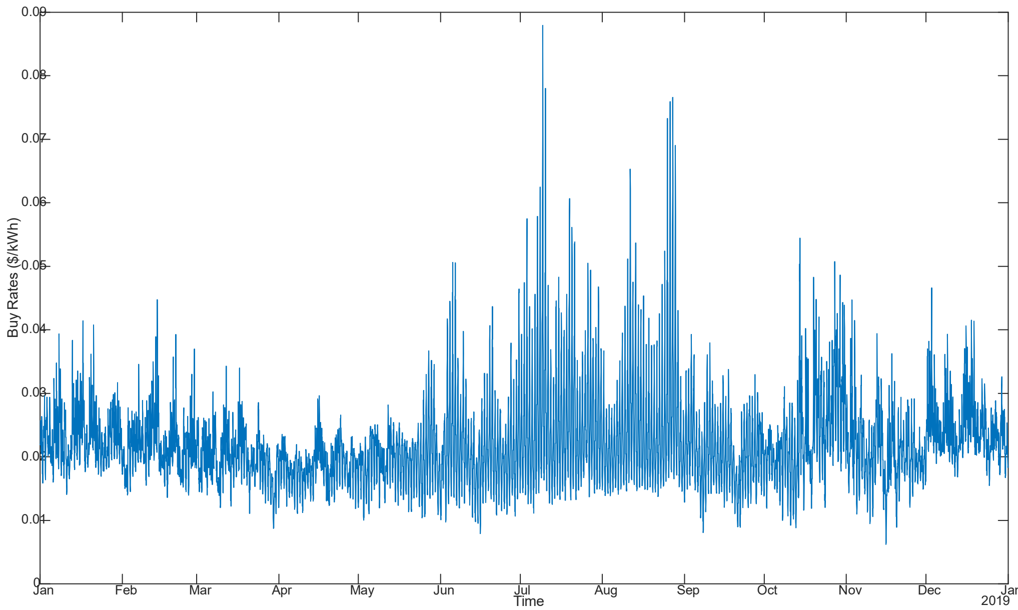


Figure 9-2: Buy Rates for one year of simulation from an Illinois utility company, Ameren [34].