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APPLICATION OF SOLAR ENERGY TO MEASURE PHOTOVOLTAIC CAPACITY AND BATTERY OPTIMIZATION

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Abstract

This study uses the Markov Decision Model (MDP) to implement battery degradation and optimize battery use in Photovoltaic and the battery system model created. The battery optimization scheme for home loads uses the application of solar energy to optimally measure photovoltaic *and battery capacity against each other. The different qualities of the standard used in this study are described starting from system characteristics and charge settings to an analysis of MDP and battery degeneration. Various systems undergo a list of analyses to implement awareness reasoning although developing battery volume and* photovoltaic *for the current system. The parametric span of cosmic and battery central tariff, the tariff of power worn taken away the framework, tariff of battery degeneration, time of year,* photovoltaic *generator size, battery size, and Health Status (SoH) of batteries were carried out to determine the optimal volume estimate and analyze the trade-offs essential in a mix scheme. This is then used to treasure trove the minimum amount of fee of the scheme with photovoltaic and battery application.*

This study support decision of the essential sizing deliberation for photovoltaic *and battery-managed home loads linked to the services grid. Insightful that the battery can be used more destructively, also it can be formed lower and run at a greater C speed. This study analyzes actual fog computing research tools and storage composition algorithms for fog computing and develops a fog computing monitoring framework to provide data for fog computing storage composition algorithms. The framework proposed in this study provides granular container virtual hardware resource information and black box monitoring of service layer information associated with microservices. Framework usefulness on Raspberry Pis and CPU overhead of framework tested.*

The results of this study present the framework proposed could be used on single-chip microcomputers with relatively inadequate computational performance. In addition, a minimal effect on the battery degeneration system on the MDP decision due to the low system C-rate limit for the battery and interesting behavior of total fee and demand is also found. For future research, testing different maximum C levels should be considered to determine the photovoltaic *size and battery system affected. Various battery optimization systems can be proved to check the benefit and disbenefits in the microgrid system case study. Lastly, collecting a scheme for actual-time reproduction to know how nice the operation is performing is the next stage of implementing MDP for battery management and system development.*

Keywords*: Solar Energy, Battery Optimization, Markov Decision Process,* Photovoltaic*, Virtual Container*

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INTRODUCTION

Apart from the practicality and essential makeup of renewable energy sources, in that falsity the issues of frequency. The result provides in this study for the irregular style of this type of formation adopting lithium-ion batteries. The concept is to stock surplus or inexpensively obtained capability and formerly adopt that capability to cut down the tariff of purchasing energy taken away by the network. Development of battery management, application of battery degeneration, and optimal size of the sustainable generator (photovoltaic in this case) are all goals of this study concerning the desire to advance the behavior of periodic sustainable energy. Lithium-ion (Li-Ion) battery technology is making continual evolution against growing density, efficiency density, and higher charge/discharge currents. These advanced have facilitated expanded area and transit distances for EVs (electric vehicles), longer battery life and capacities for power-intensive gadgets, and the ability to better utilize the intermittent behavior of renewables such as wind and solar power. Momentum is building in the area of battery storage for use with renewable energy sources. Key considerations that are important with further battery storage deployments are the costs associated with battery use, battery degeneration, and optimal battery usage and size. Improvements in this area could greatly enhance battery function in home-and-grid photovoltaic operation. Batteries are directly drawn as the number one and highest feasible benefit for developing the discrepancy between network flexibility and the absence of sustainable energy. Breeze intensity is common, specifically in lower electric capacity utilization districts (equally residential groups, industries, businesses, and so on) as long as the application fee also has authority motivation such as allowance as an element of a green energy bill. This has administered to expanding concern about the use of sustainable energy.

BACKGROUNDS

In the fog computing environment, containerized microservices are a common service deployment approach. Containers are considered a lighter implementation of the virtualization of computing resources correlated to virtual machines (VM). Storage technology uses fewer aggregating assets than VM. It can be circulated, broadcasted, and removed more quickly, which is more applicable to fog computing's dynamic computing environment. The microservices construction isolated software apps into multiple microservices which represent partition roles that connect with others even though the API acts as a complete service. This flexible deployment method can deploy different microservices on several different fog service servers, making more efficient use of computing resources. The fee of this distributed software architecture is the fee for deployment and maintenance. System administrators often have to deal with complex service dependencies. System administrators need to perform real-time analysis, deployment, expansion, and migration for various microservices on heterogeneous servers. Therefore, the fog computing storage composition algorithm brings a result to solving the issues. The storage composition conclusion will manage containerized microservices in real-time through various deployment conclusions and strategies based on monitoring data of containerized microservices.

Therefore, this study analyzes existing fog computing monitoring tools and storage composition algorithms for fog computing and develops a fog computing monitoring framework to provide data for fog computing storage composition algorithms. The framework proposed in this study show alone arranges granular storage virtual hardware resource advice, but also black box monitoring of service layer information related to microservices. This research examines the feasibility of the framework on Raspberry Pis and the CPU overhead of this framework through experimentation and shows what types of data and dashboards this framework can provide. The results show that this framework can be used on single-chip microcomputers with relatively inadequate computational performance.

RELATED WORK

Batteries are not entirely useful on their own when applied to home loads and also sustainable efficiency scheme setups. They use some sort of authority to regulate that management scheme and resolve it even if becomes protesting or draining efficiency every time. This is more delicate in a battery development system, in which the controller's goal is to make the best use of the battery, and "this first benefit could be intent on abbreviating the detectable capacity to the framework or service, helping to make better use of sustainable energy sources by compressing the duck curve effect, helping load shifting reduce operating costs, and so on (Bao et al., (2012); (Hassan et al., (2017)).

Commonly battery management systems are more complex than clean switch states, often compelling predictions on the eventual efficiency call and inventory. Because of that complication, AI (artificial intelligence) is often taken into the battery development systems. The capability of a computer to swiftly count and resolve action protocols later can be very helpful. Other research includes models such as linear programming (LP) to control the energy input and output of buildings that implement photovoltaic and manage batteries. These are compared worn on the mix with the System Advisor Model (SAM) software. This results in a fairly accurate model for an energy management system. However, two courses are required for the best results, and there is the problem of calibrating the weights needed to run the LP. A simpler battery management model was desirable for this research, especially because other parts of the system are implemented such as battery degradation. Other studies cover 2 main invitations for energy repository boards namely attention and anticipating the eventual demand for a given time. This is also for the answer in actual-time developing needs. 1st is, to adopt an east rule-based authority. The 2nd is, to adopt a competent neural network to manage scenarios in actual time. It's finding the 1-minute ML (machine learning) expected organizer is proportionate to the thirty-minute scheduled optimal rule-based controller. This lends credibility to the accuracy of the MDP model scheduled for 15 minutes since costs are not significantly reduced by trying to work a smaller sampling period.

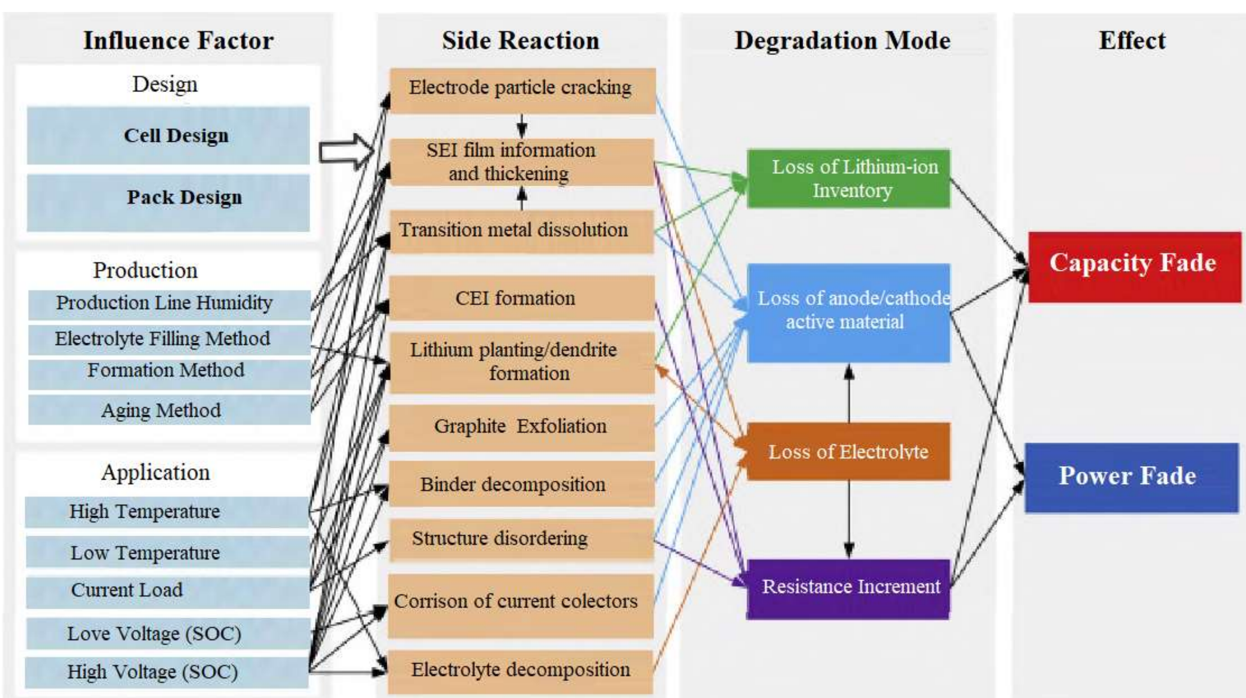

Figure 1 Description of degradation characteristics (Birkl et al., (2017))

Battery Degeneration

Lithium-ion batteries are the battery type used with MDPs because of their high energy density, general use, and because there are depictions of their degradation characteristics available for modeling. Unfortunately, like all things materialistic, batteries degrade with time and use. "Depending on its natural characteristics and other factors, degradation can include things like growth and breakdown of the Solid Electrolyte Interface (SE-I) layer, formation of cracks, metal dissolution, and others" (Birkl et al., (2017)) as can be seen in Figure 1.

The design of the SEI band is a component of the initial battery design cycle. It's important to use up the batch, but due to the SE-I layer having no time to stop growing, the battery is constantly losing usable lithium in these areas which can lead to instability and lead to an internal short circuit. Once the SEI layer has formed, stresses can build up internally causing cracks. If the battery is used aggressively or the temperature is too high or low, cracks can form more quickly. The last section mentioned is the dissolution of transition metals, i.e. "solvent oxidation, salt decomposition, and material dissolution". That's why it is less enough for applicable substantial and boosts the private protection of the battery. The result is battery degradation limiting battery life. That can be extrapolated to the fee of using the battery. Due to this fee (tariff) and revised modeling of battery characteristics for MD-P. Therein lies the problem of choosing which degradation scheme to use. There are physics-based models, simple models, single-particle models, etc.

Physics-Based Modeling

The physics-based model is the most detailed because it works at the lowest level, including many battery characteristics and their degradation that are known and can be implemented (Takahashi & Srinivasan, (2015)). All this bears to set the outcome of experimental cash unit with reproductions and analyze them to show the efficiency of the model used (Takahashi & Srinivasan, (2015); Berecibar et al., (2016)). However, "this is also accompanied by drawbacks because it is too time-consuming and heavy simulation to implement into the battery manager" as shown in the research of Berecibar et al., (2016). As Figure 1, there are an extensive amount of battery attributes that could be managed.

National Renewable Energy Laboratory (NREL)

NREL constructed a Li-ion battery model implemented for Electric Vehicle (EV) cost-minimization analysis. Prior knowledge indicates that temperature and SO-C have a large impact on EV battery life, so use the NREL model to estimate and minimize the effects of degradation. The model uses a 24-hour history of battery current, voltage, SOC, and temperature to then find capacity, resistance, and relative power. The research of Zhou et al., (2005) found that advanced battery management caused that to close more than other common systems, and when the effect of temperature degradation was minimized, cyclic degradation predominated as high-depth discharge (DOD). This means that have active interaction between DOD and battery degeneration. (Hoke et al., (201) found that the fading capacity costs were limited and crucial to check the miniature. That guide to the completion that the degenerative effects were indeed minimal.

Single Particle Model (SPM)

SPM is based on research (Bao et al., (2012)). The architecture was to clarify the physics-based model by compressing the particle aggregates to one comparable molecule, every anode and cathode side of the battery. This is done by reducing a full-order physics-based electrochemical model (with partial differential equations) to a set of ordinary differential equations. This greatly reduces the computational time of physics-based models while still being able to predict SEI layer growth and formation, crack propagation, and metal dissolution, while monitoring internal resistance, the volume fraction of solid phase, and effective diffusivity.

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Provisional Study

Within the extra definite model, here is so much advice to track down. This highly boosts the reproduction era, which, for this study, was highly undesirable as long as the previously time-comprehensive description of MDP. Nonetheless, the efficiency of the model is still desirable to capture the biggest degeneration aspects. The NREL battery model in the study of Hoke et al., (2011), although accepted by empirical statistics, the architecture of this model is clear for stemming operations of EVs (electric vehicles). SPM finally has an excellent adjustment that is no more time-exhausting to process but maintains a high expansion of efficiency against battery degeneration aspects, hence its use in this research model.

LITERATURE REVIEW

Markov Decision Process (MPD)

MD-P is an algorithmic approach to combine known and stochastic advice to anticipate eventual data. MD-P is a model of charismatic data processing used for optimization in areas such as managing battery usage. It works by dividing the areas that can be optimized in direction of time stairwell, case, behavior, and fee identical; with taking certain actions or moving to other states.

Battery Volume and Photovoltaic

When applying sustainable energy to a disposed of capacity, system size is an important consideration. For the purposes and objectives of this final project, the sizing considerations are for photovoltaics and batteries. Sizing criteria include financial, conventional positive mechanical particulars.

Size Optimization

In Kharseh and Wallbaum's (2017) study, the scheme was shaped by adopting Microsoft Excel for residentiary equity adopting actual-activity photovoltaic and load data. This study found that a given photovoltaic load without optimal battery size does not return the original contribution as fast as the same scheme with the battery applied. In Kharseh and Wallbaum's (2017) study, adopting an accurate photovoltaic and interpreted batch miniature along data, the scheme shows that load-side self-consumption and system self-sufficiency are highly dependent on the photovoltaic scheme and battery volume. 1st agreement for photovoltaic and battery scheme to stem costs bet in fee and bigger automatic-utilization collection identical with really excellent photovoltaic system sizes. In the study of Mehrabankhomartash et al., (2014) loads with photovoltaic and battery systems examined the economic brunt of power disruption. Here is an active interaction between developing battery size and lowering outage costs as photovoltaic modules and batteries are unable to amount to the capacity. If the size exceeds that the scheme has to cut the disruption fee for battery size, providing no further fee reduction. This is partly for the size housing the load completely during an outage because the load is so pricey, making larger capacity batteries more feasible.

Comparative analysis

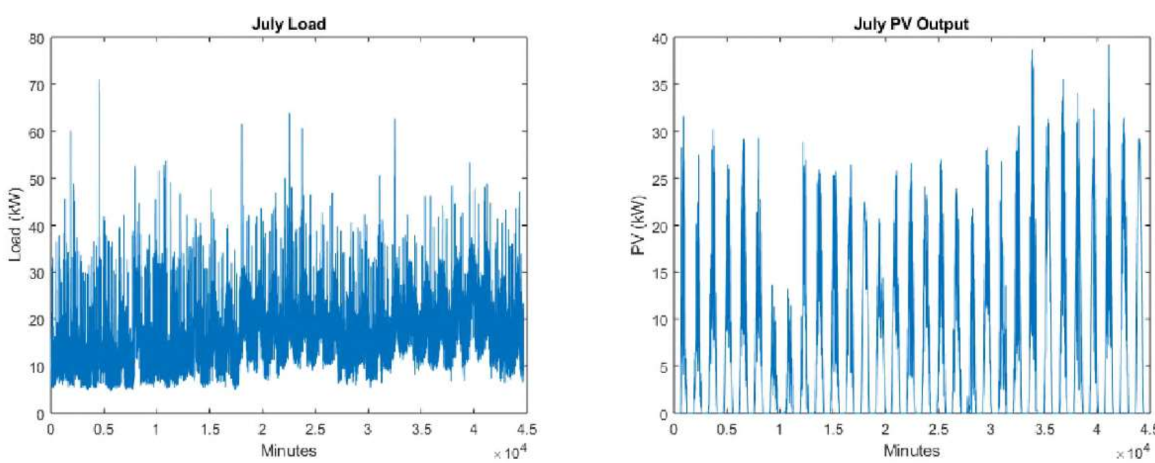
The system proposed by Kharseh and Wallbaum (2017) will challenge an arrangement of the approach proposed used in this study because it covers areas that are not the focus of the thesis for optimizing tariff devaluation and paying off the original investment. The system, which is computerized in ms. Excel and conflicts with the Matlab programming used in this study. Matlab's computational ability is necessary for the overall complexity of the programming settings used in this study. The systems used in the research by Weniger et at., (2013) and Mehrabankhomartash et al., (2014) "both have a similar approach to optimizing battery size by covering a wide range of battery sizes and seeing which areas work best". The study by Weniger et at., (2013) described "the focus is on the complementary properties of photovoltaic and batteries for fee reduction and to increase the level of self-consumption of electricity". Whereas in the research of Mehrabankhomartash et al., (2014), the ambition is to cut down the identical fee with capacity that is not given as long as the power blackout. No more scheme precisely corresponds study, the technique for an allegation of the excellent size is fairly comparable, by that two approaches targeting some sort of fee reduction. This is fascinating because the approach suggested for advancing the photovoltaic system and battery volume in this study is clean, whatever supports cut the complication of the examples that are used. Although the standard span does not include the depth and detail that some sources can obtain, the system can provide sufficient advice to perform with the case studies in this study.

ARCHITECTURE SYSTEM ATTRIBUTES

The scheme was imitated past 5 days with each imitated catching over 2 and 230 minutes to process at the present code settings. The code that was restored in each imitated was the volume of the photovoltaic also battery whatever the align from 0 times to 2 times from the initial size. The characteristics and uses of the battery are initially termed in the group of categories that the battery manufacturer prefers. So, to generate the batch assuming extra peace to those in the electric area the battery volume was changed from Ampere hour (Ah) to kilo-Watt-hour (kWh). It is also crucial to interconnect batch management with other capacities scheme characters such as PV, grid, and loads.

Load and Photovoltaic

This scheme was initially directed based on the statistics offered in the Pecan Street Data. The peak load is around 80 kW, and the photovoltaic peak is around 40 kW. The load and photovoltaic data are from June 2008 and are very difficult to work with. Due to difficulties in managing advice, the statistics worm for this study was not from Pecan Street Data, but data from Missouri S&T Solar Village. Data were collected from June 2015 to May 2016, covering a full year of Load and photovoltaic operations, with peak load and photovoltaic output peaking in the summer. The Solar Village and photovoltaic load data did not match the peaks, so factors were introduced to make the peaks align better with the June data. The load factor is 3.5, and the photovoltaic factor is -2 (negative to denote generation rather than load). The data can be seen in Figure 2 with an explanation of the July elections.



(a) Load profile for the month of July. (b) PV profile for the month of July.

Figure 2 Load and photovoltaic characteristics with various factors included.

Battery

Batteries are based on the limitations and characteristics of Lithium-ion batteries. The batch subsists of a lesser unit of batteries having an ostensible voltage of three point six volts at 50% SOC. That unit consists of twenty mini capsules that have a field of 0,049 m^2, which adds up to a unit with a field of 0.979 m^2. The battery unit is then configured ninety-eight in the set and thirty-one in coordinate, giving an initial total battery size is two hundred and fourteen-kWh. To get an improved taking the effects of degeneration, a 95% original health state (SOH) is assigned to the batch and the make batch assumes five percent debased at the start.

Cost

System fees are collected from Rolla Municipal Utilities (RMU). The standard purchase rate for electricity in the Rolla, Missouri area shows a fee of 885/kWh at a demand rate of 19.900/kW. The demand rate shows the fee associated with the highest power drawn in 15 minutes during the month. Since the simulation is only five days high it's not until 30 days, the request rate needs to change to take in that. Then, first is:

$$app\_Period = \frac{\text{SpanLen x Sim\_Span}}{Hour \text{ x } Minutes}$$

determined to get the accurate period grounded by SpanLen being the simulated fifteen minutes time period, Sim_Span being 5 simulated days in a span. Then,

$$app\_Price = \frac{\text{app\_Month x app\_Period}}{Month}$$

determined grounded by the initial application rate, App_Month, App_Period is the precalculated period in that the application level is calculated to end, and thirty days assessment of a usual season. Indirect costs include battery degradation costs, photovoltaic degradation costs, and battery energy costs. Photovoltaic degeneration was determined by adopting 31.500/W for financial photovoltaic operations; photovoltaic system power operates at forty-kW, and financial photovoltaic operations are among the ten-kW and 2-MW. The estimated lifetime for photovoltaics is thirty years, but the simulations run at a more conservative estimate of twenty-five years for a photovoltaic system lifetime. The fee of a photovoltaic system is accustomed in (price) per W and needs to be transformed to lifetime fee and next is split into (price)/span of use

$$photovoltaic\ \_C\_cap\_ = \text{photovoltaic } \_W\_C\ x\ PHOTOVOLTAIC\ \_Wattage$$

photovoltaic_C_cap_is the capital fee associated with the photovoltaic system. photovoltaic _W_C is the fee of a photovoltaic system based on AC watts for financial operation. photovoltaic _Watt is the sum of the wattage of the photovoltaic scheme. The above equation measure the comprehensive system fee. It does not reflect Leveled Energy Costs (LCOE). Then, it will be converted as:

$$Fee\_PV = \frac{q\text{photovoltaic }\_Cap\_C}{\text{photovoltaic}\_Lf\ x\ Epoch}$$

to (price)/each. Where Fee_photovoltaic is the degeneration fee of the photovoltaic scheme in (price)/span. photovoltaic _Lf is the life of the photovoltaic scheme in days. This is given as twenty-five years converted to days using 365 days in a year, which gives relatively 9131 days. Spans are days divided into 15-minute periods with 96 spans/time (day). This process predicted the fee of photovoltaic degradation to 9.20/day or 1.140/span (with spans being 15-minute time intervals). The energy fee of the battery is the initial fee for the power original battery, so it is considered important for calculating the price (fee) of adopting it.

SO-C AND SO-H

The SO-C of a batch is resolved by tracking the energy entering and leaving the battery. It is first initialized at 100% SO-C. This lowers the fee for the permanent scheme and demonstrates the demand to do things about the original energy case of the battery, necessitating calculations and costs identical to the power on batch at beginning of the reproduction. The original SO-C is also decreased to 80% to allow the battery to adjust to its usage pattern more quickly, rather than relying on stored energy reserves.

A battery's SO-H is originally appointed at one hundred percent. This demonstrated ambiguous as bound of the loop competent on battery degeneration. This causes problems with efficiency and fulfillment. 1st reaction to this is to check the fulfillment of battery health and degeneration. The degenerated model already had issues with its implementation which were fixed, leading to an examination of the model adapted to the curve adopted for the estimation of a healthy's battery. They also proved to be accurate. The problem, nonetheless, is at the barrier circumstances and conduct that are very close to the SO-H of new non-degraded batteries. This is solved by changing the SO-H from 100% to 95%.

The role of the MDP in the adoption of the batch optimally. This adapted to an undulating boundary innovation so it can run endlessly and conclude eventual battery actions. The way it works is by first dividing the day into battery operational segments called spans. The next step is to monitor battery status, the next actions that can be taken, and any charges identical to being in a certain state or for performing certain actions. 200 battery states roughly match a 214kWh battery capacity - leading to a 1.07kWh battery quantity contact per field. Each specified case is attributed to the "trash bin" in the schedule, which results in a specific state having an energy bin identical. The case is alternated when the box is joined or defective by the singular care over an operation. This action is limited in its ability to increase or decrease bays to suit battery limitations. Batteries are limited to draw/absorb only zero point three rates of C, which is characterized as ±15 cases and does not include case changes. So this means that a max of 31 various behavior can arise between each section. Nonetheless, the behavior taken must not cause the battery to eclipse or be under this space limit.

Previously the block of things that can be done in MDP is zoned, and MDP operations can begin. It looks at the battery's original state (no matter what it was when MDP started) and then makes an educated guess as to what state it should be in 24 hours forthcoming. Then it aims to evaluate the best course of action to reach the eventual case and finds the previous state of it was. This stays till the MDP returns to its original field. Before effective, the reproduction formerly adopts the activity and case to iterate after the original case is running the point, finally dominant back to MDP determine the future span action. MDP audit the appropriateness of each case and activity for all assumed spans, and MDP selects the lowest fee set of actions and states. That means with a five-day simulation there are 285,696K items for the MDP to parse (200 different states, 31 possible actions, 96 spans checked, and the 5-day simulation converts to 480spans). Nonetheless, because of MDP's aggressive computer technology, a benefit that the plan allows awful is shear from application all along the next repetition.

BATTERY DEGENERATION METHOD

Battery degeneration was applicated to see how it affects optimization and to advance battery usage accuracy. Nonetheless, issues with constructing this model were known. This includes conversion confusion between units and degradation factors which greatly increase the effect of battery degeneration. This basic margin to a re-application to individual molecule model which is formerly built into an interpreted loop adjustment that maintains the required characteristics without unduly increasing the time required to run the simulation. Accuracy is extremely upgraded, and the model is reduced to use variables frequently appreciated by those studying with batteries. Battery degeneration miniature run in 2 fields with the 1^{st} is being part of the MDP and the 2^{nd} being the present age.

Degeneration as Element MDP

The degeneration adopted in the MDP is an interpreted adjustment of the SPM curve. This includes the SO-C, specific unit voltage, battery capacity, and battery pack power as output. MDP covers a kind of large field in the reproduction so it is considered cautious to cut down MDP computation time by reducing the battery degeneration model. Left out of this reduced loop adjustment, the simulation took more than 120 minutes. In integrating and reducing the simulation time, it is not necessary for MDP to have an accurate model, because it is demanding to complete how future degeneration aims to change the fee of using the battery. Since future predictions are no longer accurate, all that is needed is to have a model that is careful enough to form the support a reliable action scheme for making battery usage decisions.

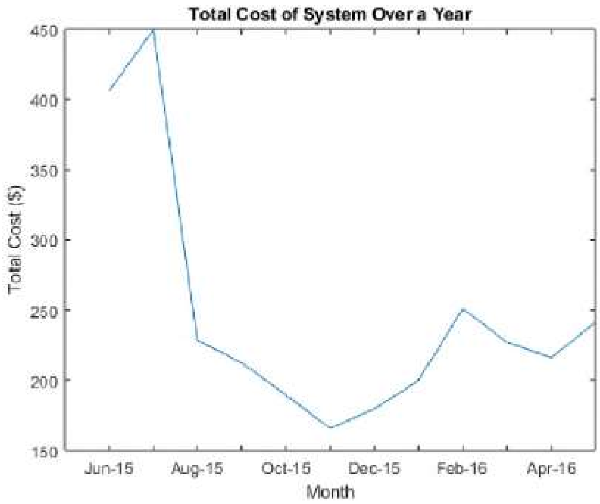
Degeneration as Part of the Present Age

Once a decision is made about what battery to use in the next span extra careful model is desired due to the clone as a perfect is no more hunching what the battery will do because it's making decisions about it via MDP. As the choice of model battery life is common and determined simultaneously, a more careful degeneration system can be supplied. The degeneration model affirms SOC, battery unit voltage, batch size, crack multiplication, metal partition multiplication, and SEI layer formation.

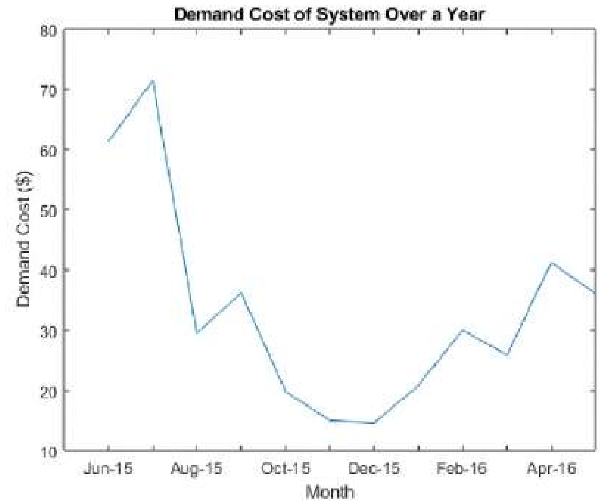
PHOTOVOLTAIC OPTIMIZATION AND BATTERY SIZE

This simulation is a case study of how to approach photovoltaic and battery size optimization simultaneously with each other with battery optimization and battery regeneration systems. Factors influencing this are costs associated with electricity usage (normal purchase rate, demand rate, resale rate, etc.), time of year (affecting load usage and photovoltaic output), the load being worked on (changeable control battery and photovoltaic volume), SO-C start, battery degeneration, etc. photovoltaic and battery size dimension from zero to 2 times the initial size (photovoltaic initially 40kWh) in the accretion of 0,25 (figure 9).

To begin with photovoltaic measurement and battery size development, 2 factors are considered. 1^{st} is the application of current information initialing from the leading regions. 2nd is to locate the original case of battery degeneration. Since this project is a case study of the feasibility of photovoltaic and battery setup in and around Rolla, MO, the photovoltaic and load data must be from around the area. Thus, increasing the importance of the case studies to the field where the data is collected is considered prudent. This change provides capacity and photovoltaic data from within Rolla, MO, itself. With the application of updated data, the starting point of battery degeneration can be reached. There are many problems with fitting degradation curves by testing to get SO-H close to one hundred percent. Degeneration will not function properly because it reaches and is near the limit of the fit curve and the fee of degeneration is so low that it is almost insignificant when correlated to another fee (Figure 11).

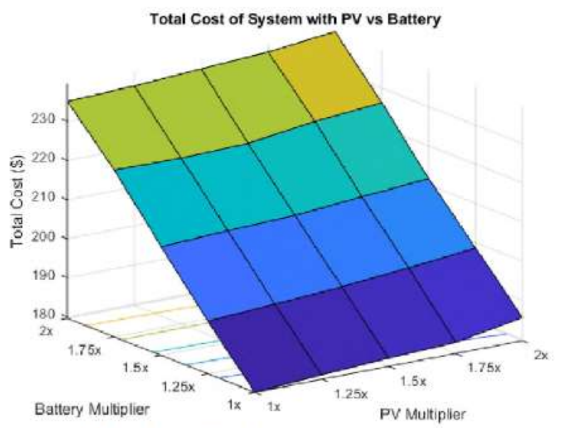


(a) Total cost for system over a year.

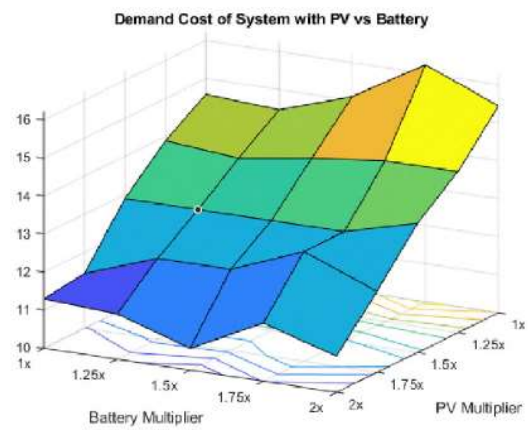


(b) Demand cost for system over a year.

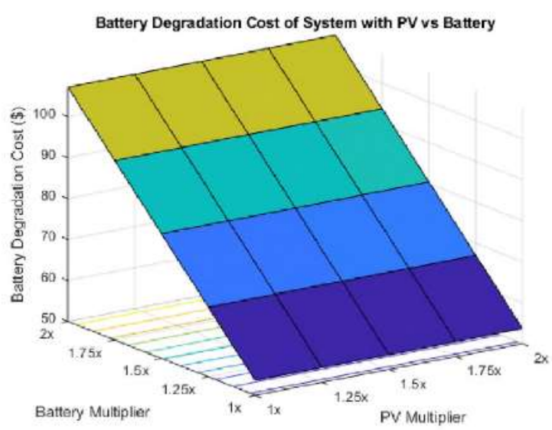
Figure 3 Correlation of fee component for a year of simulation



(a) Total cost for PV and battery changing from 1 to 2 times original sizing.



(b) Demand cost for PV and battery changing from 1 to 2 times original sizing.



(c) Battery degradation cost for PV and battery changing from 1 to 2 times original sizing.

Figure 4 Main fee is identical with changing photovoltaic **and battery sizes from 1 time to 2 times their original size.**

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That leads to the adoption of 95% SO-H batteries. This strikes a balance to show the effects of battery degeneration out of the battery becoming so debased or being the mass of the charge. Figures 10 and 11 show the degeneration graph. After the photovoltaic, load data, and initialization of degeneration are collected, then next is advancing photovoltaic and the battery is to treasure trove the right time of year has peak load, The system information provided is deduced into total op fee and appeal every month or year (Figure 3). This composed July is a bit pricey time to complete as well as a big time to advanced photovoltaic and battery size. In 7th and 8th of July were chosen such that the 7th is initially used and indicates implementation of the data, and the 8th is used to indicate that data is being applied. With the setup complete, the optimization of the photovoltaic and battery size operations can begin. Originally, the dimension of monitored conduct is from the initial size to double in 0.25 increments as seen in Figure 4. Due to the illogical appeal fee aspects between the photovoltaic Multiplier 1.75x and 2x with an increment of 0,25 for Figure 4b, more trial is carried out for a photovoltaic Multiplier of 1.75x to 2x with an increment of 0,125 times (figure 6).

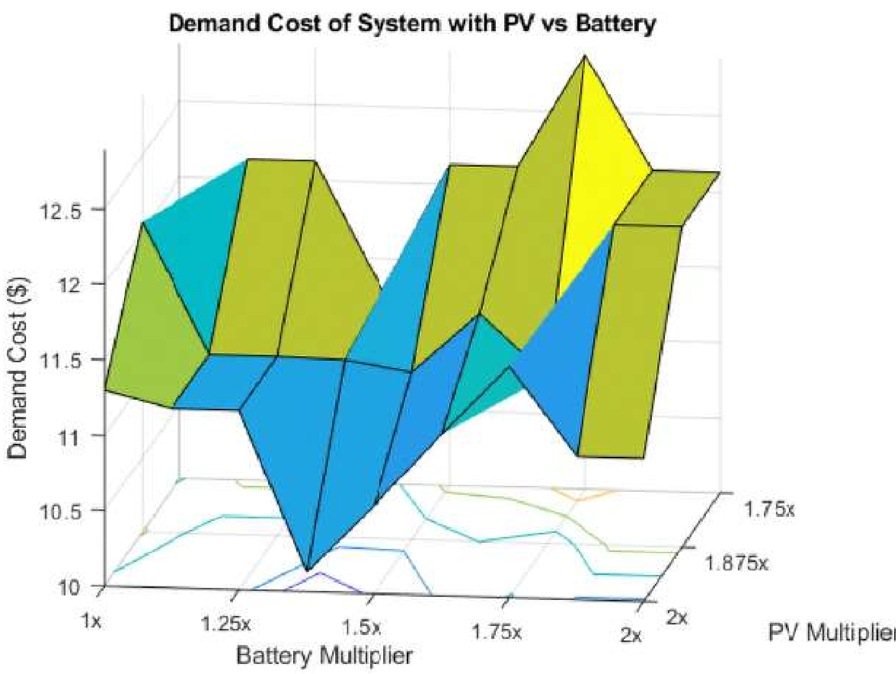

Figure 5 Request fee for photovoltaic **change from 1,75 times original size to 2 times and battery replacement from 1 time to 2 times both in zero point one hundred and twenty-five increments.**

This guided the recognition that even if there is a minimum charge on the 2x photovoltaic Multiplier and 1.375x Battery Multiplier, there is commonly insufficient data for a full investigation. While it seems feasible to continue increasing v size and battery settings from 1x to 2 times to 1 time to 3 times range for PM and BM, it was completed that there was some background missing in charge behavior for battery and photovoltaic implementations. There is unacceptable analysis in the field before coverage is provided. So, the entire circuit of the clone is restored to 0 times to 2 times photovoltaic and the original battery designation. There are also multiple focal points narrowing the battery size from 0,5 times to 1 time its initial quantity in 0,1 increments, having the photovoltaic follow a 0 time to 2 times scheme and 0.25 increments. This can be seen in Figure 12a and Figure 12b.

RESULTS CONTRIBUTION AND SENSITIVITY TEST

Photovoltaic and battery expansion schemes are conventional to get the fair smallest one and the other of the sum of scheme fee and demand costs on the point of the ambition is to decrease them. With the original limit, there are unsuitable points tested to acquire the mini point. Nonetheless, this data dimension covers the size characteristics of the original system for both photovoltaic and battery. This is presented in Figures 6 and 7.

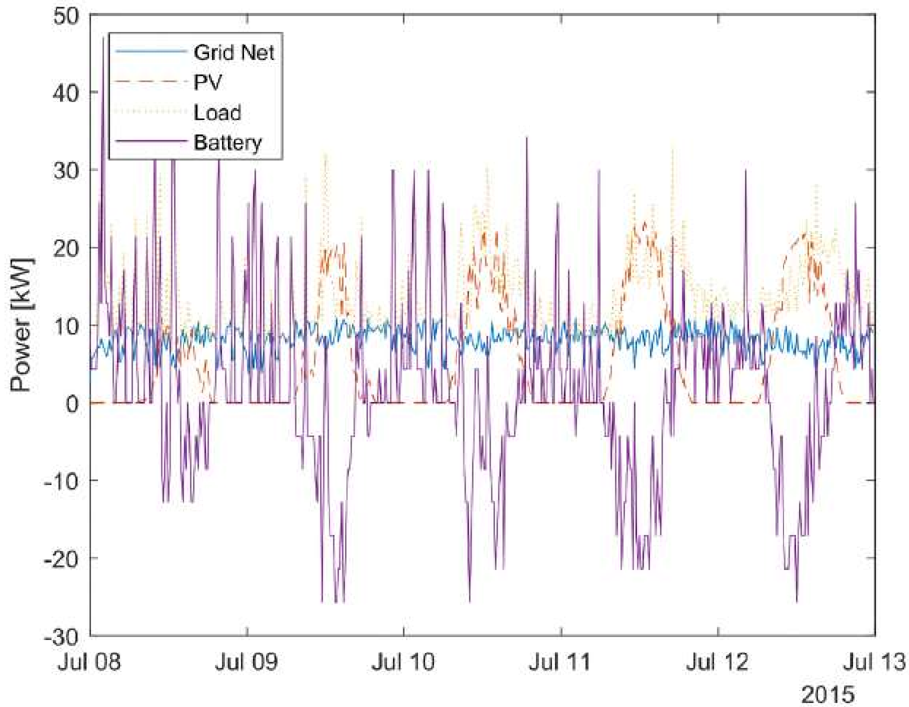

Figure 6 Simulated power characteristics for 5- days with real photovoltaic and battery size.

Photovoltaic and battery power flows are the opposite of another characteristic depicted in capacity tests. With the full limit tested where the photovoltaic and battery sizes change from zero to two times their original size, the total fee of the system ends up with the desired minimum point blocked out in Figure 8 and Table 1.

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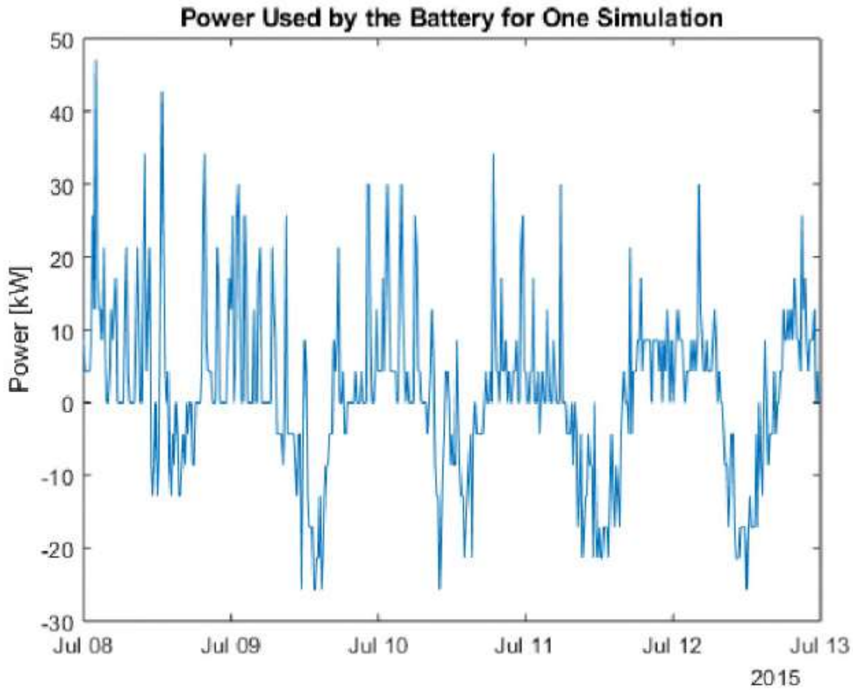

Figure 7 Battery capability practice during a five-day imitated with real photovoltaic **and battery size.**

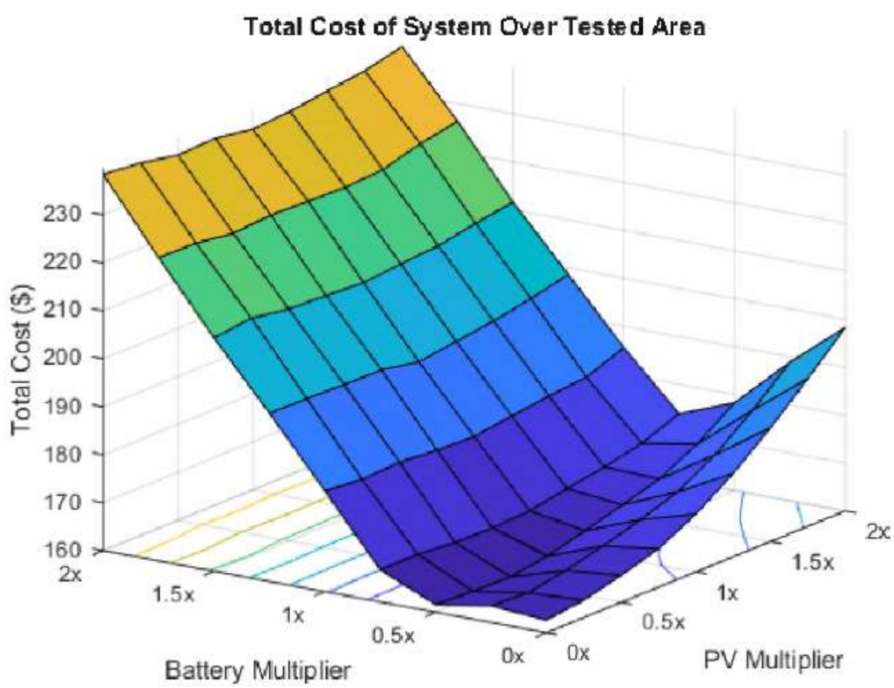

Figure 8 The amount of fee battery and photovoltaic replacement from zero to two times the initial size.

The trough in the 0,5 times Battery Multiplier is where the minimum is located focusing the field that is shielded by the photovoltaic Multiplier from 0x to 0.5x. Looking at Table 1, there are some additional important points. One is at 0.75x photovoltaic Multiplier at 0,5 time Battery Multiplier, and the other is at home where no photovoltaic or battery is applied.

Table 1 The amount of fee for the photovoltaic and battery replacement from zero to two times the initial size with the minimum value advertised.

Battery \ PV	0x	0.25x	0.5x	0.75x	1.0x	1.25x	1.5x	1.75x	2.0x
0x	162.62	163.62	165.63	167.99	172.02	177.38	183.74	190.81	198.28
0.25x	163.49	163.04	164.49	166.44	168.74	171.38	175.94	182.06	188.89
0.5x	161.57	161.19	161.07	162.21	164.30	166.52	168.79	172.87	178.29
0.75x	166.74	166.76	166.04	165.93	166.33	167.78	169.10	170.91	173.88
1x	181.04	180.23	180.66	180.02	179.65	180.78	181.77	182.51	185.52
1.25x	195.09	194.95	194.69	194.58	193.10	194.18	195.27	196.81	198.61
1.5x	208.62	209.59	208.32	207.96	207.49	208.20	208.82	210.31	211.57
1.75x	223.20	223.11	221.94	222.59	222.32	222.06	222.52	224.81	226.28
2x	238.44	237.67	236.11	236.48	235.18	235.75	236.84	237.86	239.70

An unpredictable outcome is the loss of a minimum for the appeal tariff. With the first set of parameters, there is a bizarre set of behavior that seems to exhibit some possible minimum credits for an area of photovoltaic and batch size rate ranging from 1 to 2 times the initial assessment in zero point twenty-five times increments. As mentioned before, this causes the threshold to change from zero to two times the photovoltaic and original size of the battery in the twin addition of zero point twenty-five. With these additional data points, the request fee drops dramatically up to the size of the battery is 75 percent times the initial size collected. Then, demand costs are almost down and seem autonomous of photovoltaic applications. For photovoltaics, this has a more moderate fee reduction effect and is biformed with battery volume as it is most adequate when the battery is over the 0,75 point at the native size. PVs shift in effectiveness around their original size and decrease in persuasiveness same with several PVs supplied development (figure 9). For strong representations, the appeal estimate originally downturns speedily.

There also appears to be almost no battery degeneration effect on the MDP battery development system. This is the minimum response of using simulated batteries on battery degeneration. The reduction of degeneration effect is also partly due to the suitable battery degradation curve setting applied in MDP as it is relatively insensitive to C-rate. This led to a lack of visible degradation in the MDP as a whole. This is shown in Figure 10. The notion that degradation is not significant enough to affect the optimization scheme begins when the tests performed on the initial capacity of the battery are alternated to see if the MDP aims to advance the component and management system of the battery. The capability ranges from zero point five to one point five of this original quantity and the runs over the photovoltaic and the battery size go from the initial size to twice its original size. This series of simulations demonstrates the lack of degradation effects as the battery action schemes do not deviate from each other other than scaling. Each differs from the others by its scaling factor. This can be seen in Figure 11.

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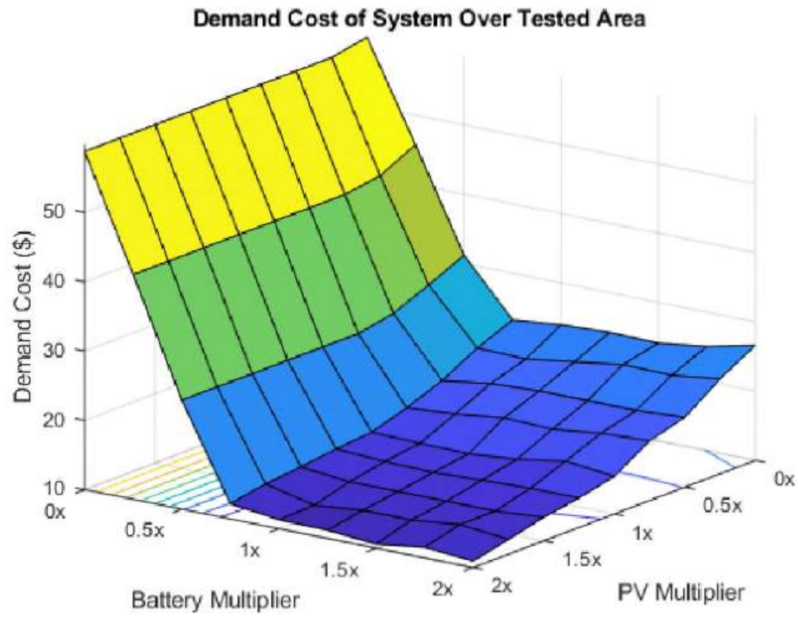


Figure 9 Request fee for battery and photovoltaic replacement from zero to two times the original size.

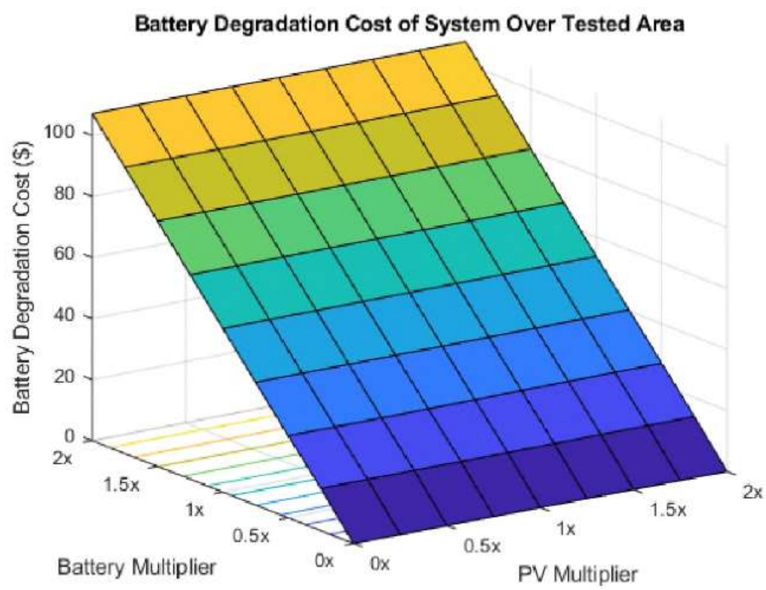
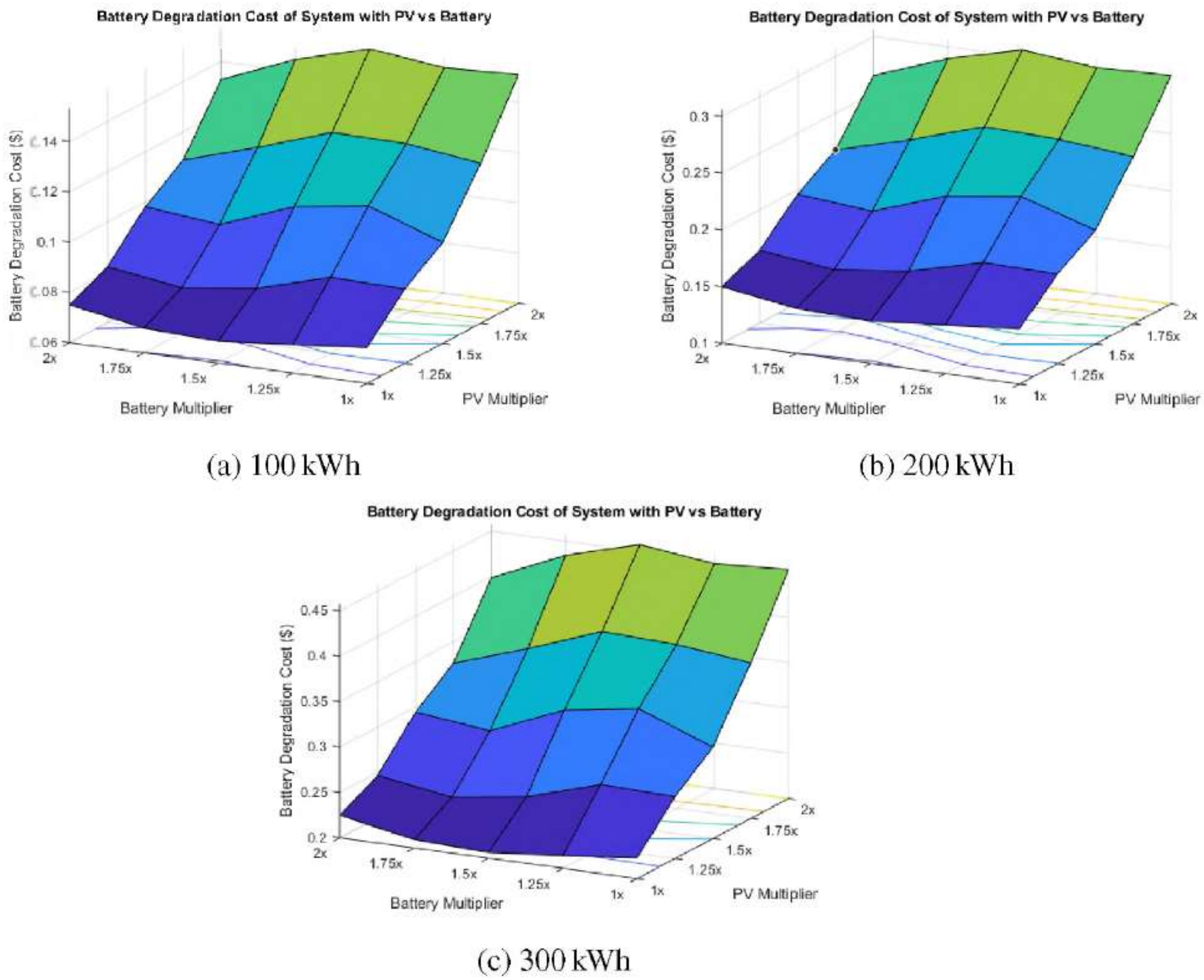


Figure 9 Battery degradation costs for battery and photovoltaic replacement from zero to two times the original size.

But the limit only ranges taken away 1 time to 2 times rather than 0 times to 2 times for photovoltaic Multiplier (PM) and Battery Multiplier (BM). Both of these issues are fixed in Figure 8 and Figure 9. The data cap has changed from 0x to 2x with an increase of 0.25 for the photovoltaic added and Battery added. One of the other points of interest is the Battery Multiplier function which seems to fragment in the charge-application loop for Figure 9. This causes the sequence of analysis to whet in on distinct junctions. This can be seen in Figure 1. Upon closer inspection of the verge of over 0,75 times in BM the appeal charge curve design shown in Figure 12b still looks operate like a piecemeal function with a leveling-off of about 0.7x on the Battery Multiplier instead of 0.75x. Though at a lower photovoltaic Multiplier it seems to behave more like a curve. Further analysis shows that there is a discrepancy between demand and the total fee "optimal" point. The total fee optimal region includes a trough centered on the 0.6x Battery Multiplier along a dimension of photovoltaic Multiplier values, including a 2.401.350 minimum, visible

Totals in Figure 12a. The demand charge rate drops to about 0.7x on Battery Multiplier as well at a reasonable range of photovoltaic Multiplier values but an 18.700 minimum is on a 2x photovoltaic Multiplier and 1.5x Battery Multiplier in Figure 9 or 169.500 feet with a 2x photovoltaic Multiplier and 1x Battery Multiplier in Figure 12b. Nonetheless, as long as the systems with bigger cosmic boards and batteries, the edge of the explosion-off field on the application charge curve is treated as a more excellent operating point. This results in an optimal demand fee of 218.700 at the 1x photovoltaic Multiplier and 0.7x Battery Multiplier in Figure 12b.



(a) 100 kWh (b) 200 kWh

(c) 300 kWh

Figure 12 Total fee and application for photovoltaic **going from zero to two times the initial size in 0,25 accession and battery replacement from 0,5 times to 1-time initial size in 0,1 increments.**

CONCLUSION

Past studies are detailed in areas such as battery development systems, application of battery degeneration, and photovoltaic volumizing and batch assimilation to provide a concept of how this research fits into the done research. different parts of the model used in the thesis are described starting from system characteristics and charge settings to an overview of MDP and battery degradation. The most notable contribution of this study is the minimal effect of the battery degeneration system on MDP selections as the low system C-rate limit for batteries. Pleasing management of total fee and application. The total charge has a minimal value centered on a 0.6x Battery Multiplier, or 128kWh battery capacity, ranging from 0 times to 0,75 times photovoltaic Multiplier, and zero kW to thirty kiloWatt crest photovoltaic appropriately. Demand charges decrease after a Battery Multiplier of 0.7 times, or 150kWh, and a photovoltaic Multiplier of 1x, or 40kW. Although the minimum demand charge is 1.5x Battery Multiplier or 321 kWh, and 2x photovoltaic Multiplier or 80 kW, the more feasible option is to approach the intersection in Fig 12b where the requirement charge is out of the zone.

Knowing the battery can be used better and more destructively due to less degradation affecting the excellent battery management system, the battery itself can be made lower and rush at a higher C speed. This research also helps address regional size considerations for photovoltaic and battery activity as it is a case study in the area surrounding Rolla, MO. This can help determine the continuity of photovoltaic and battery operations for areas with similar characteristics such as photovoltaic output, load, and grid costs. However, an even greater contribution is the advance of battery expansion schemes by optimizing battery size by photovoltaic operation, while optimizing battery usage. So computing another layer of intensity into the advancement of battery development systems such as MDP. Future research will consist of measuring the various max of C levels and seeing how that affects the photovoltaic size and battery systems. Various battery development systems can be proved to see the advantages and disadvantages of each in a microgrid system case study. The final suggestion is to incorporate the scheme into the actual time imitated to know how well the operating work is at the next level in implementing MDP for battery management and scheme development.

BIBLIOGRAPHY

A. Hoke, A. Brissette, D. Maksimovic, A. Pratt, and K. Smith, “Electric vehicle charge optimization including effects of lithium-ion battery degradation,” in 2011 IEEE Vehicle Power and Propulsion Conference, pp. 1-8, Sept. 2011.

A. Sani Hassan, L. Cipcigan, and N. Jenkins, “Optimal battery storage operations for photovoltaic systems with tariff incentives,” Applied Energy, vol. 203, pp. 422-441, 2017.

CR Birkl, MR Roberts, E. McTurk, PG Bruce, and DA Howey, “Degradation diagnostics for lithium-ion cells,” Journal of Power Sources, vol. 341, pp. 373-386, 2017.

Claas Hüter, Shuo Fu, Martin Finsterbusch, Egbert Figgemeier, Luke Wells, & Robert Spatschek. (2017). Electrode–electrolyte interface stability in solid state electrolyte systems: influence of coating thickness under varying residual stresses. AIMS Materials Science, 4(4), 867–877. https://doi.org/10.3934/matersci.2017.4.867

Ezugwu, V., & Igbinosun, L. (2017). Portfolio allocation under the vendor-managed inventory: A Markov decision process. Journal of Applied Sciences and Environmental Management; Vol 20, No 4 (2016); 1127-1135; 1119-8362.

G. Bao, C. Lu, Z. Yuan, and Z. Lu, “Battery energy storage system load shifting control based on real-time load forecast and dynamic programming,” in 2012 IEEE International Conference on Automation Science and Engineering (CASE), pp. 815820, 2012.

Hodge, D., & Le, H. (2016). Markov decision process algorithms for wealth allocation problems with defaultable bonds. https://doi.org/10.1017/apr.2016.6

J. Weniger, T. Tjaden, and V. Quaschning, “Sizing of residential photovoltaic battery systems,” Energy Procedia, vol. 46, pp. 78-87, 2014. 8th International Renewable Energy Storage Conference and Exhibition (IRES 2013).

K. Takahashi and V. Srinivasan, “Examination of graphite particle cracking as a failure mode in lithium-ion batteries: A model-experimental study,” Journal of The Electrochemical Society, vol. 162, no. 4, pp. A635-A645, 2015.

Lu, J., Feng, T., Timmermans, HPJ, & Yang, Z. (2017). An integrated Markov decision process and nested logit consumer response model of air ticket pricing. Lu, J, Feng, T, Timmermans, HPJ & Yang, Z 2017, 'An Integrated Markov Decision Process and Nested Logit Consumer Response Model of Air Ticket Pricing', Transportmetrica A: Transport Science, Vol. 13, No. 6, pp. 544-567. Https://Doi.Org/10.1080/23249935.2017.1306727 .

M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, “Critical review of the state of health estimation methods of li-ion batteries for real applications,” Renewable and Sustainable Energy Reviews, vol. 56, pp. 572-587, 2016.

M. Kharseh and PH Wallbaum, “The effect of different working parameters on the optimal size of a battery for grid-connected photovoltaic systems,” Energy Procedia, vol. 122, pp. 595-600, 2017. CISBAT 2017 International Conference Future Buildings & Districts - Energy Efficiency from Nano to Urban Scale.

M. Mehrabankhomartash, M. Rayati, A. Sheikhi, and AM Ranjbar, “Practical battery size optimization of a photovoltaic system by considering individual customer damage function,” Renewable and Sustainable Energy Reviews, vol. 67, pp. 36-50, 2017.

Wu, X., Zhou, J., Keane, JC, Dhere, RG, Albin, DS, Gessert, TA, DeHart, C., Duda, A., Ward, JJ, Yan, Y., Teeter, G., Levi, DH, Asher, S., Perkins, C., Moutinho, HR, & To, B. (2005). Advances in CdTe R&D at NREL. Related Information: Presented at the 2005 DOE Solar Energy Technologies Program Review Meeting Held November 7-10, 2005 in Denver, Colorado.