INTELLIGENT DISPATCH FOR DISTRIBUTED RENEWABLE RESOURCES

by

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Abstract

A time may soon come where prices of electricity vary by time of day or season. Time of Day (TOD) pricing is considered by many to be a key part of creating a more energy-efficient and renewable-energy-friendly grid. TOD pricing is also an integral part of Smart Grid and is already available to some customers. With TOD pricing becoming a reality, intelligent dispatching systems that utilize Energy Storage Devices (ESDs) to maximize the use of renewable resources, such as energy produced by small, customer owned wind generators and roof-top solar generators, and grid energy while determining the most economical dispatch schedule could play an important role for both the customer and the utility. This purpose of this work is to create an algorithm upon which these dispatching systems can be based. The details of one proposed algorithm are presented. The full development of the algorithm from its most simplistic form into a much more complex system that takes into account all of the major non-idealities of a real system is given. Additionally, several case studies are presented to show the effectiveness of the algorithm from both a technical standpoint and an economic standpoint. The case studies simulated both wind and solar powered devices using data taken in the state of Kansas, but case studies to emulate electric rates and renewable resources in other areas of the country are presented as well. For each of these case studies, 20 year net present value calculations are presented to determine the economic viability of both the renewable energy production and the dispatching systems.

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Dedication

To my wonderful parents, who have made my education possible and helped me to reach so high into my potential; if my mom hadn't yelled at me with such force in the third grade for not turning in my homework, I would have never made it this far.

Acronyms

AGM	Absorbed Glass Mat
C/x	Charging Rate
DG	Distributed Generation
DOD	Depth of Discharge
ESD	Energy Storage Device
GA	Genetic Algorithm
GEL	Gelled Type Battery
IDDRR	Intelligent Dispatch for Distributed Renewable Resources
LP	Linear Program(ming)
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
PV	Photovoltaic
RTP	Real Time Pricing
SLA	Sealed Lead Acid
SOC	State of Charge
TOD	Time of Day pricing
UPS	Uninterruptible Power Supply

Nomenclature

E_L	Energy Supplied to Load
E_R	Energy taken from renewable sources
E_B	Energy transfer from the ESD
E_{B+}	Energy taken from ESD
E_{B-}	Energy put into ESD
R_P	Price rate of purchasing energy
R_S	Price rate of selling energy
E_{B0}	Initial ESD charge
E_{BC}	Battery capacity
E_{B0max}	Maximum battery capacity
E_{B0min}	Minimum stored energy
E_{Bdis_max}	*maximum hourly, or other period, discharge*
E_{Bchar_max}	*maximum hourly, or other period, charge*
R_B	Cycling cost coefficient
e_{dis}	Efficiency of discharging from ESD
e_{char}	Efficiency of charging ESD

Matrix Shorthand Notations

Identity Matrix: $$eye(r \times c) = \begin{array}{cc} c & \\ \begin{bmatrix} 1 & 0 & . & . & 0 \\ 0 & 1 & & & . \\ . & & . & & . \\ . & & & . & 0 \\ 0 & . & . & 0 & 1 \end{bmatrix} & r \end{array}$$

Lower Triangular Matrix: $$tril(r \times c) = \begin{array}{cc} c & \\ \begin{bmatrix} 1 & 0 & . & . & 0 \\ 1 & 1 & & & . \\ 1 & 1 & 1 & & . \\ . & & & . & 0 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} & r \end{array}$$

Upper Triangular Matrix: $$triu(r \times c) = \begin{array}{cc} c & \\ \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ . & & . & & . \\ . & & & 1 & 1 \\ 0 & 0 & . & . & 1 \end{bmatrix} & r \end{array}$$

Matrix of Zeros: $$zeros(r \times c) = \begin{array}{cc} c & \\ \begin{bmatrix} 0 & 0 & . & . & 0 \\ 0 & 0 & & & . \\ . & & . & & . \\ . & & & . & . \\ 0 & . & . & . & 0 \end{bmatrix} & r \end{array}$$

CHAPTER 1 - Background

It is possible, and becoming increasingly popular in today's world, for anybody to have his or her very own renewable generator such as a residential-sized wind turbine or solar system. Many people choose to own these types of systems as a means of becoming less reliant on the grid and to shrink their carbon footprint. However, the initial cost of these systems often makes them hard to justify from an economic standpoint; in fact in many cases the initial investment is never recouped [1]. It is possible, though, to better utilize the energy production from these systems so that the owner sees a faster return on investment by adding some sort of Energy Storage Device (ESD), as a medium through which these renewable resources are dispatched, along with an optimization algorithm to determine when is best to use the excess generation. In fact, residential-sized battery systems are currently available for backup power and off-grid systems. Additionally, electric rates that increase during the peak usage times of the day would have the added benefit to the utility of encouraging peak load shaving/shifting automatically through this dispatching system.

In fact, Time of Day (TOD) pricing in which the price of electricity is known to customers in advance and Real Time Pricing (RTP) in which the price fluctuates in real time are considered by many to be a key part of creating a more energy-efficient and renewable-energy-friendly grid and the implementation of these types of rates is an integral part of many Smart Grid schemes. TOD pricing is already being offered to some customers as an alternative rate structure by some utilities such as Alliant Energy and Ameren Illinois Utilities. These rate structures help to curb demand during peak consumption time when it costs the utility the most to provide energy, since customers postpone the use of energy-intensive activities until rates are lower. TOD pricing also helps by relieving some stress on the electric grid, possibly even deferring some capacity expansions, and promotes the installation of distributed renewable generation as customers want to avoid higher cost of energy times by supplementing their electric needs with their own fuel-free generators. Additionally, appliances that automatically run during low cost-of-energy times, in order to shift load, could become commonplace.

If TOD pricing becomes a reality, intelligent dispatching systems that maximize the use of renewable resources while determining the most economical dispatch schedule could play an important role for both the customer and the utility. While renewable energy is typically not considered dispatchable, batteries or other types of Energy Storage Devices (ESDs) enable it to be.

The purpose of this work is to create the algorithm on which these dispatching systems can be based, a topic that has received little attention as of yet. While this work focuses on distributed customer-owned systems, it is also designed to work within the network described by Figure 1.1 below.

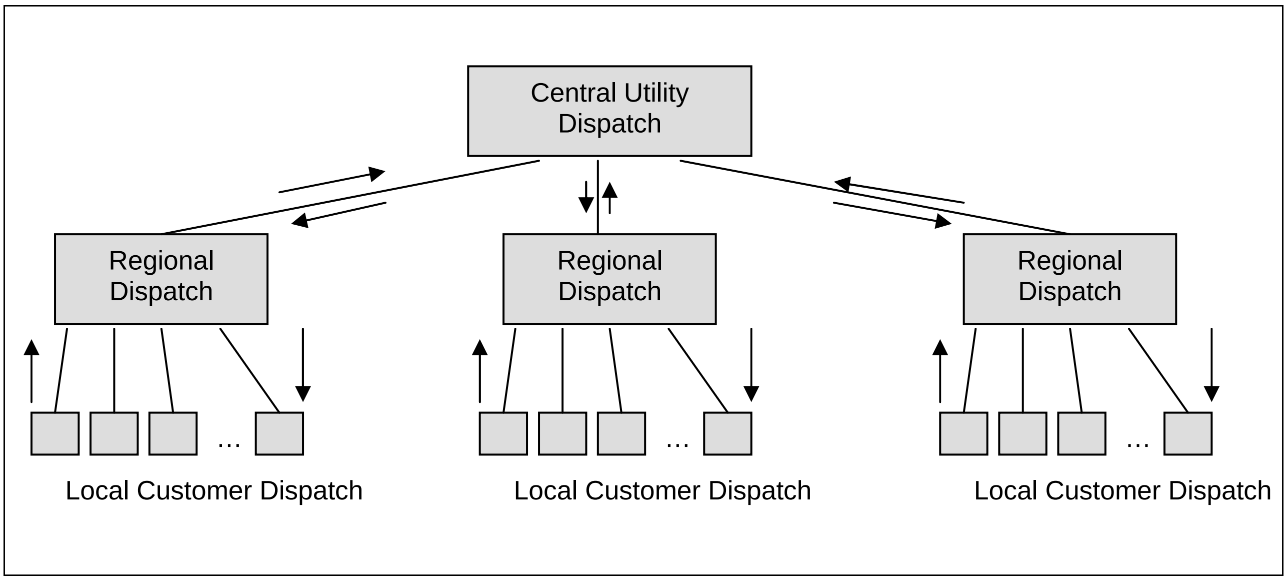

Figure 1.1: System Hierarchy

In the three-tiered Distributed Generation (DG) control system presented above, the top level, denoted as the Central Utility Dispatch, controls the dispatching of the entire fleet of generators available to the utility to best incorporate the large utility sized and small scale customer-owned renewable generators. It could also set limits on the maximum amount of excess DG the system is willing to accept, and it would seek to keep the transmission system operating conditions, such as voltage and frequency, within proper limits.

The next level denoted the Regional Level, is the go between from the utility level to the customer level and incorporates all loads on a single bus, substation transformer, or substation. This level seeks to coordinate the various customer level generators so that the distribution system is kept within proper operating limits and it could also put limits on the amount of energy the utility will accept from each of the customer-owned units in a given hour.

Finally, the algorithm presented in this report is designed to control the lowest level, the Local Customer Dispatch. Each Local Customer Dispatch accounts for a single customer-owned DG/ESD system. The customer owned system would receive information though a data link on the electric rates from the regional level as well as information on the expected renewable resources such as wind speed and/or solar insolation, also known as solar irradiance, for the area. The customer owned system would inform the utility of the planned dispatch schedule so the utility could plan accordingly.

Additionally, it has been envisioned by some that a national grid similar to the Interstate Highway System will be constructed to best utilize areas with an abundance of renewable resources. Should that eventually happen, the Central Utility Dispatch from neighboring utilities could be connected in parallel, or another tier to represent a power pool could be added to become a connecting node between various utilities and further optimize the use of all generators.

Goals of the Algorithm for Intelligent Dispatch for Distributed Renewable Resources (IDDRR Algorithm)

As mentioned previously, the purpose of this work is to design an algorithm that determines the most economical dispatch solution for a customer-owned renewable generation unit as seen from the customer's point of view while using all of the available renewable resources. With this algorithm (also referred to as the IDDRR Algorithm) in place the customer would be able to see a faster return on his or her investment in a Distributed Generation (DG) system. The utility, which controls the electric rates, would see a decrease in power usage at meters with this system in place during peak load times, as that would most likely be the highest cost of energy time. This helps to relieve some stress on the grid during those peak usage times and shift customer load to off peak hours. In fact, with control over energy rates, the utility would basically have control over the customer's dispatching system and by varying these rates with some sort or TOD pricing scheme could promote the flow of more or less energy from the DG into the grid at specific times.

Inputs/Outputs

To create the dispatch schedule, the algorithm needs several inputs, which could come from both internal and external sources. For example, the Regional Dispatch, shown in Figure 1.1, could relay information such as load and resource forecasts, or these could be determined at the Local Dispatch level by some historical and/or statistical method.

System Inputs

1. Load forecast
2. Renewable resources forecast (wind speeds, solar radiation, etc.)
3. Purchasing price of energy
4. Selling price of energy
5. Initial battery charge
6. Non-idealities (efficiencies etc.)

System Outputs

1. Dispatch schedule

Decision Making Process

With the predicted load, resources, and other inputs made available to the dispatching system, the IDDRR algorithm creates a dispatch for any desired length of time; however 24 hours is most likely to be used in a real system running this algorithm. The system attempts to operate based on this dispatch until new input data is available, and then the system recalculates the dispatch. For example, a 24 hour, hour-by-hour dispatch is created with the most recent data available. The system works off of that dispatch until an hour later, when new data becomes available, then the system recalculates the dispatch and works off of that. Updating the dispatch as often as possible insures that the dispatch is as accurate as possible.

Algorithm Basics

It may be possible to use several different optimization algorithms to solve this problem, but it was determined that the best balance between performance and ease of implementation is to use a linear program (LP). More information on LP and how it is used to implement the dispatching algorithm is available in Chapter 4. However, it is emphasized that the use of LP requires the linearization of system characteristics, which may not be linear in reality.

Report Outline

The research presented here is separated into several chapters, the most important of which is Chapter 4 in which the IDDRR algorithm is developed. Chapters 1 through 3 are dedicated to presenting the problem and the background information necessary for designing the algorithm and simulating it on realistic systems. If the reader has a good understanding of batteries and other energy storage devices as well as residential sized renewable generators, Chapter 2 may be passed over. Chapter 5 presents the technical and economic results of systems utilizing the designed algorithm, as well as data used for the simulations. The data presented in Chapter 5 is also useful in setting up additional simulations in the future. Finally, Chapter 6 is a brief summary of the work and results and it helps to establish a link into the next phase of this research.

CHAPTER 2 - A Glimpse of Current and Future Technology

Before a dispatching algorithm may be applied, simulated, or even developed for a renewable energy system, the technologies available for these systems must be understood, as the specifications of these technologies account for many of the inputs and constraints that the dispatching algorithm takes into account. This chapter covers all the major components that are found in these types of systems.

Customer-owned renewable energy systems might consist of some sort of renewable generator such as a wind turbine or solar panel system, some type of Energy Storage Device (ESD) such as a battery or flywheel, and other components such as inverters to convert solar or battery DC power to AC grid power and chargers for storing energy in a battery. Additionally, improvements and breakthroughs in these types of technology may be available in the near future and are therefore studied as well. However, since this dispatching algorithm is only intended for residential and small commercial use, only those types of systems available for residential and small commercial customers are reviewed here.

There are several characteristics of the energy storage system which need extra attention as they form the constraints used by the algorithm to create a dispatch. Also, because the dispatching algorithm uses LP, these characteristics have to be linearized in some way based on their typical characteristics if they are not naturally linear. These characteristics are:

1. Efficiency – the overall efficiency of storing energy and using it later, which includes storage efficiency, inverter efficiency, and charger efficiency
2. Capacity – the maximum amount that may be stored
3. Cost – the initial cost to purchase and install the system as well as the cost of using it (cycling cost)
4. Max charge/discharge – the maximum amount that may be stored in some type of storage medium or taken out of that medium in a given time period
5. Lifespan – the number of years the system is expected to last and in the case of storage mediums, the number of charge/discharge cycles expected over its lifetime

6. Minimum State of Charge (SOC) – the minimum amount that must be left in the storage medium

ESD

Electric energy produced by renewable energy systems can be stored in several types of ESDs. The most common type of ESD found in residential systems at the present time is lead acid type batteries and therefore these are covered in much more detail than any other type of ESD. However, since other types of residential ESDs are available, they are examined briefly as well. It should be noted that pumped water and superconducting magnetic energy storage, among others, are not studied here as these are not usually available for residential applications.

Batteries

Many different battery chemistries are currently available on the market for various applications. Some well-known battery chemistries at this time include lead-acid, nickel-metal hydride (NiMH) and lithium-ion (Li-ion). While the high energy capacity to weight ratio, or gravimetric weight ratio measured in Wh/kg [2], makes NiMH and Li-ion cells ideal for laptops and cell phones, the most prevalent type of battery found in residential storage applications is by far lead-acid due to its low cost and low maintenance requirements [3]. However, there are even several different types of lead-acid batteries designed for various purposes. For instance, automobile batteries are designed for short powerful bursts of energy but not for deep discharges and would therefore be inappropriate as backup power supplies for homes. On the other hand, batteries specifically designed for deep discharges are generally incapable of the high-powered bursts required to run large electric motors and other power intensive electric loads.

A basic lead-acid battery consists of several 2 volt cells packaged together in series to form 6, 12, or 24-volt batteries depending on the number of cells. Batteries can then be wired together in series to create 12, 24, or 48-volt strings which in turn can be wired together in parallel to increase capacity and current output. The complete combination of batteries is called a battery bank. Each cell is composed of two lead plates, the electrodes, with an acidic electrolyte in between. When a current runs through the battery, either to charge or discharge it, an electrochemical reaction occurs between the acid and the electrodes. However, this reaction slowly destroys the positive lead electrode [4], which leads to what is known as a battery's cycle life. A battery's cycle life, or lifespan, can be directly attributed to the thickness of the positive plate.

A full cycle is defined as a full charge and discharge of the battery. Every battery is rated at a certain number of cycles. However, the actual cycle life depends on how quickly the battery is charged or discharged and to what level, which in turn leads to Depth of Discharge (DOD) and charge/discharge rates (C/x)[1].

Depth of Discharge

DOD is the level to which a battery is discharged. For instance, if a battery is discharged from 100% charge to 20% charge it is said to be at 80% DOD. Starting batteries, such as those used in automobiles, should never be discharged below 50%, while deep cycle batteries may be designed for up to 80% DOD [5]. It should also be noted that the cycle life for batteries, as specified by the manufacturer, is reported at a specific DOD rather than a full charge and discharge. Exceeding the recommended DOD for any battery greatly decreases the battery's cycle life. Figure 2.1 below, taken from a deep-discharge flooded battery specification sheet, shows just how much cycle life can vary depending on DOD.

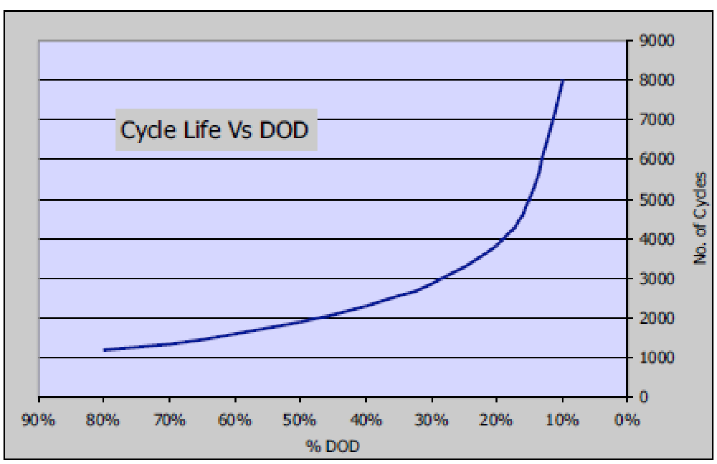

Figure 2.1: Cycle Life vs. DOD [6]

[1] DOD and C/x ratings can be directly attributed to the thickness and surface area of the lead plates. Batteries with greater plate surface area are able to provide higher currents and therefore have a higher C/x rating. Batteries with thick, solid electrodes have a longer cycle life and are therefore capable of deeper DOD. Unfortunately, batteries can only be designed for one or the other; thick, solid plates or sponge-like plates with a large surface area [4].

Maximum Charging/Discharging

The maximum rate at which a battery should be charged or discharged is given as some fraction of the battery's amp-hour capacity. For instance, a manufacturer may recommend that a battery not be charged faster than C/5. This means the current should not exceed one-fifth of the battery's capacity. So for a 220Ah battery, a C/5 current would be 44A.

In general, manufacturers recommend that a charging rate of C/5 not be exceeded, and after reaching a state of charge (SOC) greater than 85% it should be cut back further, eventually to C/100 [7]. However, some batteries can be charged at a rate of up to 4C [4], assuming the battery cables are able to handle that much current.

Discharging rates on the other hand work somewhat differently. A battery's capacity is reported at various discharge rates. For example a battery might have a capacity of 1kWh at a 5-hour discharge rate, but the capacity at the 20-hour rate might be 1.3kWh. This effect is due to diffusion rates of the electrolyte within the battery. At high rates of discharge, the electrolyte cannot move quickly enough to the lead plate, and therefore the chemical reaction is not supplied quickly enough, to keep the voltage of the battery up [51]. Any constraint placed on the discharging rate provides a maximum level of capacity.

Other Characteristics Considered

Another aspect of batteries to consider for inclusion in the dispatching algorithms is self discharge. Self discharge is the natural occurrence of the battery bleeding off charge over time due to chemical reactions inside the battery. However, since the self discharge rate of batteries is so low, about 5% per month [2], and this dispatch cycles the battery almost daily, it is not necessary to include this in the dispatch decision-making process.

Temperature also has a large impact on battery performance. Batteries are rated at room temperature, but the capacity of a battery drops in colder temperatures and increases in higher temperatures. On the other hand, battery life span decreases at higher temperatures and vice versa. Temperature characteristics add a lot of unnecessary complication to the dispatch and therefore it is assumed the battery stays at room temperature, so temperature characteristics are ignored.

Lead-Acid Battery Type Comparisons (AGM vs. GEL vs. Flooded)

Lead-acid batteries are further divided up into three groups: flooded (also known as wet cell) batteries, gelled (GEL) type batteries, and Absorbed Glass Mat (AGM) batteries. Flooded batteries have been around longer than any other type of lead-acid battery. AGM and GEL batteries are a newer type of lead-acid technology and perform much better than the flooded type, but they do so at a higher price. One characteristic which AGM and GEL share is that, unlike flooded lead-acid batteries, there is no liquid electrolyte. This makes them much safer to work with and transport, as a crack in the case of the battery does not result in an acid spill. In AGM batteries a mat saturated with an acidic solution is sandwiched between the lead electrodes. The mat holds all the acid in place so that solution cannot escape from it. One problem that eventually occurs in AGM batteries is that as the positive electrode erodes away, as it does in all batteries, it eventually begins to pull away from the mat, hurting performance and in time creating an open circuit across the entire cell.

GEL type batteries use a semi-solid gelled solution between the electrodes. Since the GEL electrolyte is not firm like the mat in an AGM battery, the electrode never pulls away from the electrolyte. However, high currents passing through the battery can create permanent voids in the GEL that decrease its performance. Generally, GEL type batteries are used more in high DOD type applications where high current is not a necessity, such as solar powered residential backup systems, and AGM type batteries are used in applications where shorter, higher-powered bursts of energy are required such as driving large electric motors.

Flooded type batteries can be designed for both deep-discharge and high current output, but do not exceed the performance of GEL or AGM in either case. Figure 2.2 summarizes which lead-acid battery types should be used for various applications. However, contrary to other manufacturers, Concord discontinued the manufacture of GEL batteries after research and development on their AGM batteries produced models that outperformed their GEL counterparts in all categories [52]; but since AGM type batteries are typically not optimal in high DOD applications, they are not discussed in detail from here on.

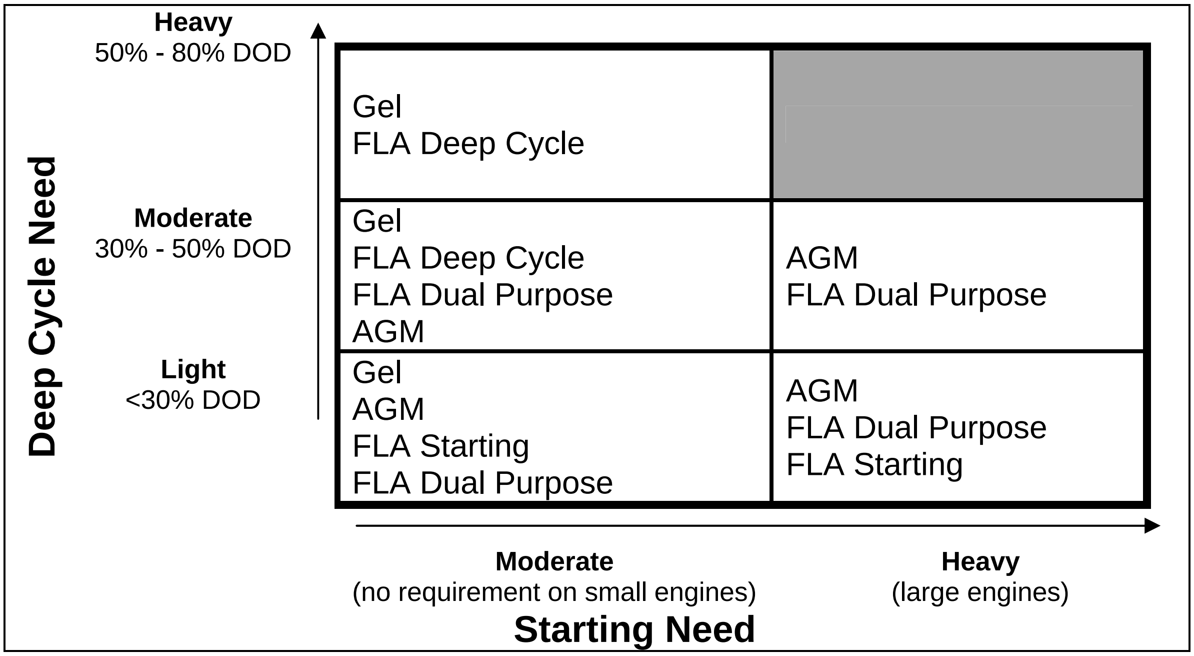

Figure 2.2: Battery Type vs. Application [2]

Battery cycle life varies by type and by how the batteries are used. According to the manufacturer of Deka batteries, their GEL type should last 600 cycles (when limited to 80% DOD) [8], but according to another source GEL type last 500 to 1500 cycles when limited to the same DOD [9]. This discrepancy could be because the manufacturer would rather quote a number on the low end so that a large majority of their batteries last at least that long. Deka deep-cycle flooded batteries are expected to last 1500 cycles at 80% DOD [10]. To compare in more general terms, when compared to Deka GEL and Deka AGM type batteries, the flooded type received a score of “very good” while AGM was scored as “excellent” and GEL was scored as “best” [11].

Typical VRLA Battery Cycling Ability vs. Depth of Discharge*

	Typical Life Cycles	
Capacity Withdrawn	Gel	AGM
100%	450	150
80%	600	200
50%	1000	370
25%	2100	925
10%	5700	3100

Figure 2.3: Cycle life vs. DOD for Deka GEL and AGM batteries [8]

Battery efficiencies also vary with type and how the battery is used. A battery is typically quoted as having a total AC-AC round trip efficiency of 60 to 80% [12] including inverters and chargers. The efficiency of the battery itself is therefore obviously higher. The Trojan 30XHS flooded battery was found in one study to have a total charge efficiency of 85%, which is quoted often for wet cell batteries [13]. AGM batteries on the other hand can have efficiencies of over 96% [14]. Deka quotes battery efficiencies for their products as 95.2% for GEL, 90.9% for AGM, and 76.9 to 83.3% for flooded [11].

The study on the Trojan 30XHS also shows how non-linear battery efficiency is. The study found that at a low State of Charge (SOC) from 0 to 84%, battery efficiency is 91%, but falls to 55% from 79 to 84% SOC. However, since the dispatching algorithm investigated in this research only accepts linear constraints, typical battery efficiencies are used.

Manufacturers and Available Batteries

Several battery manufactures exist, but the two most studied for this research were by far Deka and Trojan due to the fact that they produce GEL, AGM, and Wet cell batteries, making comparison easier. Also, both companies produce batteries specifically for renewable energy applications, and make a large amount of technical documentation on each of their batteries available on the internet. Tables 2.1 and 2.2 below show several flooded and GEL type batteries along with the energy capacity and cost of each. In all cases the energy capacity is quoted at the 5 or 6 hour discharge rate, depending on what number is reported by the manufacturer, since the batteries are intended to charge during off-peak hours and discharge during the 2 to 8 peak hours of the day. Capacities were determined by measuring Ah output down to 1.75 volts per cell [15], or 100% DOD, and multiplying by the battery's rated voltage (i.e. 6 or 12 volts).

Table 2.1: Flooded Type Comparisons (* indicates 6 volt battery; + indicates 6 hour rate)

Battery	**Capacity (Wh)**	**Cost ($)**	**Cost/kWh**
Deka 8L16	1770*+ [16]	289.00[a]	163.28
Trojan T105	1110* [17]	130.00[a]	117.12
Trojan 30XHS	1260 [18]	186.95[c]	148.35
Rolls Surrette 6CS-25PS	3294* [19]	1309.00[b]	397.39

[a] innovativesolar.com; [b] www.theresourcestore.ca; [c] ebatteriestogo.com

Table 2.2: Gelled Type Comparisons (* indicates 6 volt battery; + indicates 6 hour rate)

Battery	Capacity (Wh)	Cost ($)	Cost/kWh
Deka 8G8D	2376+ [20]	576.11[d]	242.47
Trojan 24-Gel	792 [21]	154.79[e]	195.44
Deka 8GU1H	342.72+ [20]	$83.40[a]	243.35

[a] innovativesolar.com; [d] http://store.altestore.com; [e] www.plymouthbatterycentre.co.uk

Super-capacitors / Ultra-capacitors

Super-capacitors, known also at ultra-capacitors, are a scaled up version of the small capacitors found in most electronics and are generally used nowadays only for short duration power interruptions. In their present state they would not be favorable as the primary ESD in peak shaving applications. However, they can be combined with other forms of ESD such as batteries to create a system that is capable of both short bursts of power, via the super-capacitor, and long duration output during power outages, via the battery. This has an added side effect of increasing the life of the battery by decreasing the number of cycles the battery is subject to, as the super-capacitor completely handles all short duration ESD utilization [22]. As of 2004, the largest commercially available super-capacitors were capable of 100 kW, but they could only output that amount of power for 10 seconds (i.e. maximum energy storage of only 278 Wh) [12].

As of today, super-capacitor technology is mostly in the developmental stage, but the potential of this technology looks promising and these may one day overtake batteries both in the laboratory and commercially. Researchers at Los Alamos National Laboratory developed a super-capacitor capable of 2.7 million cycles in 1999 [23] and Maxwell Technologies is currently producing super-capacitors with energy densities ranging from 0.87 to 5.52 Wh/kg with their largest product capable of storing and discharging up to 147 Wh of energy [24], albeit at a price of over $7,000. One specific super-capacitor worth mentioning is the EESU being developed by a company called EEStor. The patent for this device, filed in 2001, claims the device will be capable of storing 52.5 kWh of energy with a total weight of only 339 pounds, for an energy density of 344Wh/kg [25]. Table 2.3 shows this in comparison to other battery technologies available. The estimated price of the EESU at high volume production rates is $2100 [26]. This means an ESD with 10 times the energy density of a lead-acid gel battery and less than half the cost of the cheapest lead-acid flooded battery may soon be available. Currently the company claims to have a working prototype and has been invested in by several high profile companies including Lockheed Martin, but the production version of the EESU has missed several deadlines and many feel it may be all hype.

Table 2.3: EESU vs. Leading Battery Technologies [25]

	NiMH	Lead-Acid (GEL)	EESU	Ni-Z
Weight (lbs)	1716	3646	336	1920
Volume (in^3)	17,881	43,045	2005	34,780
Self Discharge Rate (per 30 days)	5%	1%	0.1%	1%
Charging time (full)	1.5 hr	8.0 hr	3-6 min	1.5 hr
Life reduced with deep cycle use	Moderate	High	None	Moderate
Hazardous Materials	Yes	Yes	None	Yes

Hydrogen Fuel Cell

Hydrogen fuel cells are similar to batteries in that a chemical reaction occurs to create an electric current. However, in the case of hydrogen fuel cells, the reaction is between hydrogen and oxygen to create water, known as hydrolysis, which also releases energy. The major difference between fuel cells and batteries is that battery life is dependent on the amount of electrolytic solution and lead contained within the battery, but a fuel cell can be continually replenished with hydrogen and oxygen [22] giving it a much longer lifetime. While hydrogen can be produced with fossil fuels, a truly clean hydrogen fuel cell would use hydrogen generated by the “charging” of the fuel cell in which water is broken down into oxygen and hydrogen by passing a current though it, otherwise known as electrolysis. The typical AC-AC round trip efficiency of a clean hydrogen fuel cell is expected to be 60 to 85% [12]. Commercially available fuel cells range from as low as several watts to as high as 2400 kW [27], but these systems typically extract hydrogen from fuels such as natural gas rather than storing energy via electrolysis.

Flywheels

A flywheel consists of a very heavy rotating mass mechanically coupled to a motor/generator. The flywheel is "charged" by spinning it up to higher and higher speeds via the motor. The kinetic energy contained in the flywheel can then be discharged as electric energy through the motor operating in reverse as an electric generator. Generally, flywheels are used in the event of a power outage to provide 1 to 30 seconds of ride-through time before back-up generators come online [22], but they have also enjoyed success in applications including power quality and as an Uninterruptible Power Supply (UPS). Small flywheels ranging from 1 kW over 3 hours to 100 kW over 30 seconds are available commercially and larger flywheels are being developed [12].

Renewable Generators

Renewable powered generators built for residential and small commercial uses generally come in the form of wind powered and solar-electric machines. The manufacturers and dealers of these units often offer expected payback times, but the amount of time it actually takes to pay off the unit depends heavily on siting issues such as the amount of renewable resources available, the electric rates, and the load. These units are covered in more detail below.

Wind Turbines

At this time there are several wind turbines available for residential and small commercial use. These range in rated power output from 100W to 50kW, the larger of these units being set up at large farms or at schools. For this research, two machines are investigated: the Southwest Windpower Skystream 3.7 and the Bergey Excel-S.

Southwest Windpower: Skystream 3.7

The Skystream 3.7, shown in Figure 2.4, is rated at 2.4kW at a rated wind speed of 13 m/s (29mph) [28]. It is specifically designed for residential use; hence the curved blades which reduce noise to a level that typically cannot be heard over the sound of the wind [29]. Additionally the Skystream 3.7 comes with a 5 year warranty [29], although it was designed with only 2 moving parts and is expected to last 20 years without major maintenance [53]. Several tower options ranging from 30 to 70 feet are available through Southwest Windpower and include both monopole and guyed structures. The typical installed cost of a Skystream 3.7 varies from $12,000 to $18,000 [29].

Figure 2.4: Skystream 3.7 [Author's Picture]

The power curve for the Skystream 3.7 is given in Figure 2.5. This curve shows the power production of the turbine at various wind speeds. At 60 mph the turbine goes into emergency shut down because running at higher wind speeds could cause damage to the turbine.

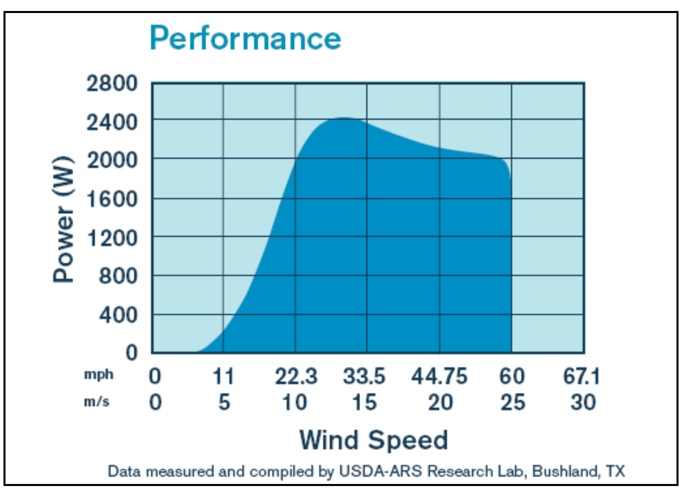

Figure 2.5: Skystream 3.7 Power Curve [28]

Bergey: Excel-S

The Excel wind turbine, manufactured by Bergey, comes in two forms. The Excel-R is specifically designed for battery charging in off-grid systems and the Excel-S is designed for grid-connected systems. Both include built-in inverters, but the Excel-R also includes a battery charger. However, the systems this research is intended to study include both a grid connection and battery charging. To make things comparatively simple, the simulations are run on only the Excel-S. This way, the same charger is used in all systems studied.

The Excel is nearly maintenance-free with the stationary components designed to last 50 years and the moving components, of which there are only four, designed to last 30 years. In a five year test program conducted by Wisconsin Power & Light, the Excel showed an availability of 99.1% which is 9.0% higher than any other turbine tested. Also, the test program found the Excel to have an O&M cost of only 0.0026 $/kWh [30].

The Bergey Excel-S is rated at 10 kW in 13.8 m/s (31mph) wind. It should be noted that the Excel-R is only rated at 7.5 kW; this is due to a load matching problem between the alternator and battery banks. Turbine prices, which include the inverter, range from $23,500 to $29,500. As with the Skystream, several tower options are available and range in price from $10,150 to $17,200 [30]. Typical installed costs for the Bergey Excel range from $48,000 to $65,000 [30].

Figure 2.6: Bergey Excel [http://www.westwindrenewable.com/images/excel.color.jpg]

Figure 2.7 shows the power curves for both the Excel-S and Excel-R, but the Excel-R is not simulated in this research. As with the Skystream 3.7, the Excel has a shut-down wind speed. For the Excel, this is just over 44 mph.

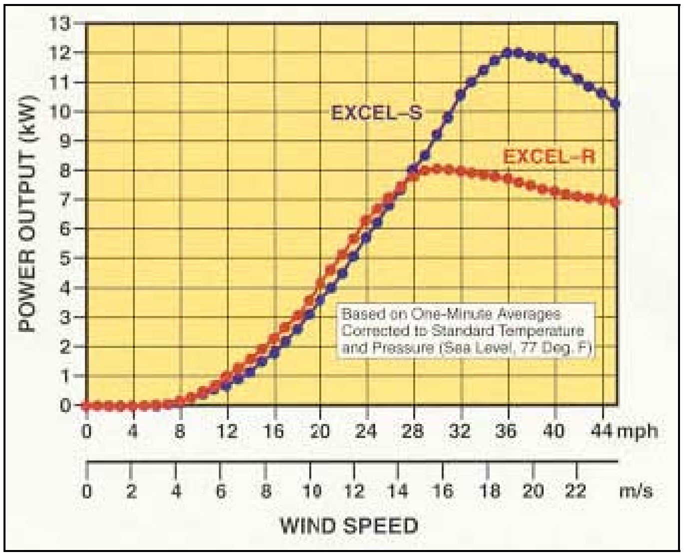

Figure 2.7: Bergey Excel Power Curve [31]

Solar-Electric Systems

Solar power systems come in two forms, solar-electric and solar-thermal. At the present solar thermal is more efficient in large-scale operations, but in residential applications is typically used only for heating purposes. Therefore, only solar-electric systems are studied from here on.

While wind turbines are often specified with power curves relative to wind speed, as seen previously for the Excel and the Skystream, solar panels are often only specified at a certain power output. However, this does not mean the system always produces its rated output. The actual production depends on the amount of sun falling on the panels and the angle at which it makes contact (also known as the angle of incidence), the load, and the temperature.

A typical V-I curve for a solar panel is shown in Figure 2.8. The endpoints of the curve are the short-circuit current, for which the voltage drops to zero, and the open-circuit voltage, for which the current is zero. The actual power output is of course the product of voltage and current.

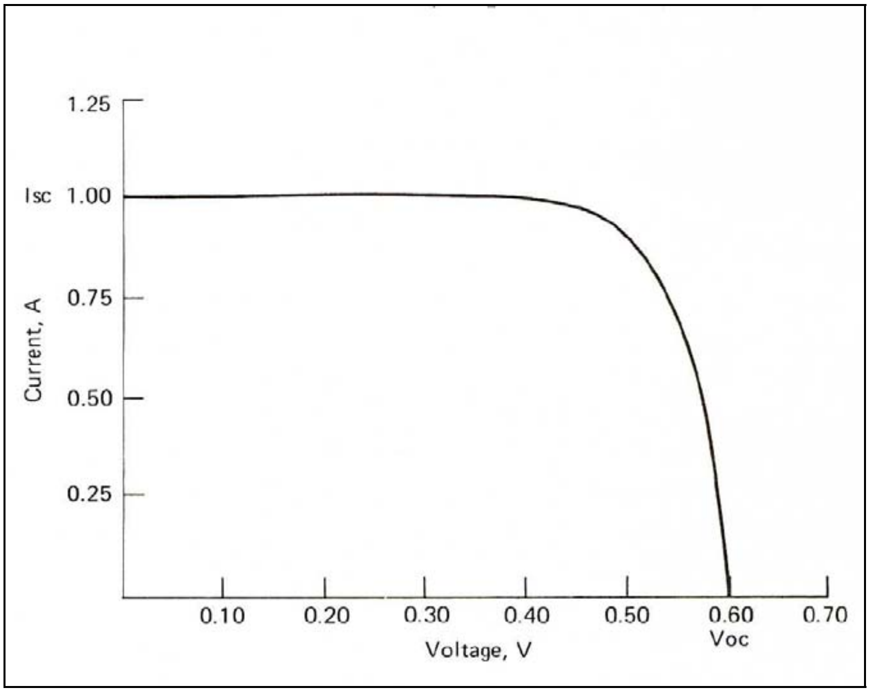

Figure 2.8: Solar Cell V-I Curve [32]

As shown in Figure 2.9, the power output is not constant over all operating voltages. There is a well defined peak power point along the elbow of the curve.

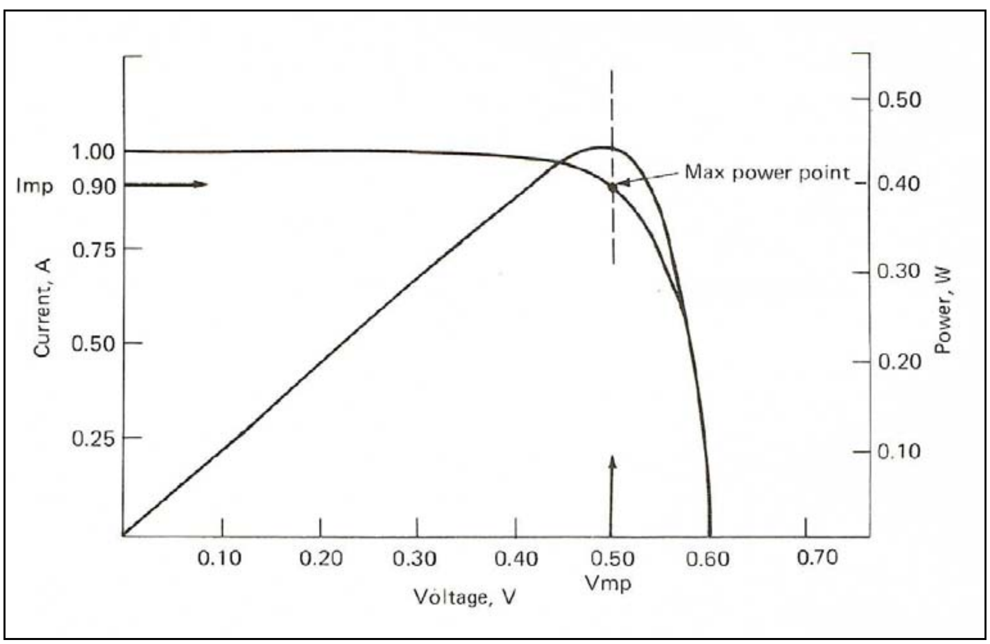

Figure 2.9: Solar Cell Maximum Power Point [32]

However, where the system is actually operating depends on the load as shown in Figure 2.10.

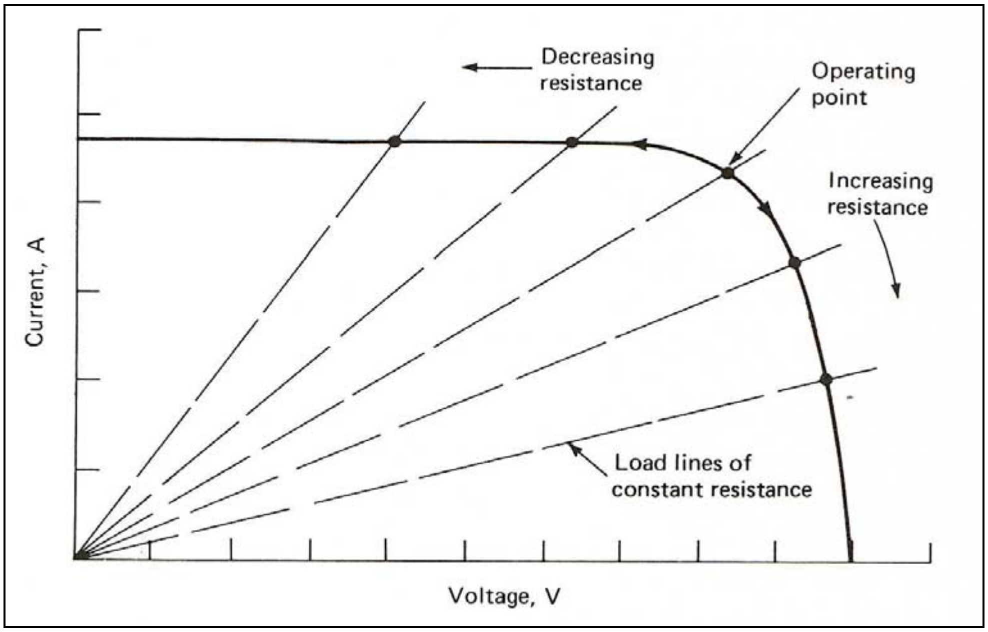

Figure 2.10: Operating Point vs. Resistance [32]

Additionally, the V-I curve changes in relation to the amount of sun falling on the solar cell, as seen in Figure 2.11, and on the temperature at which the system is operating, as seen in Figure 2.12.

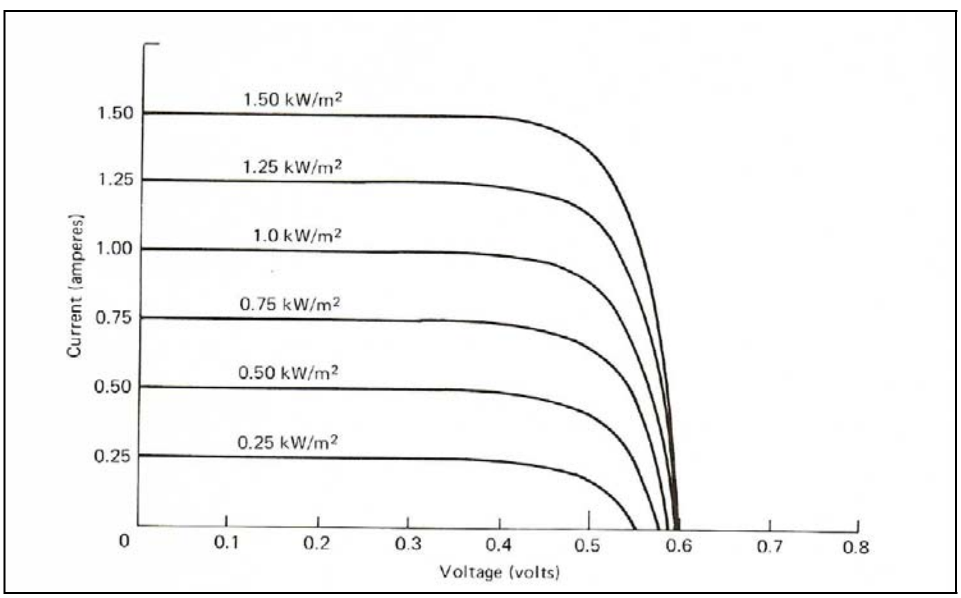

Figure 2.11: V-I Curve vs. Solar Irradiance [32]

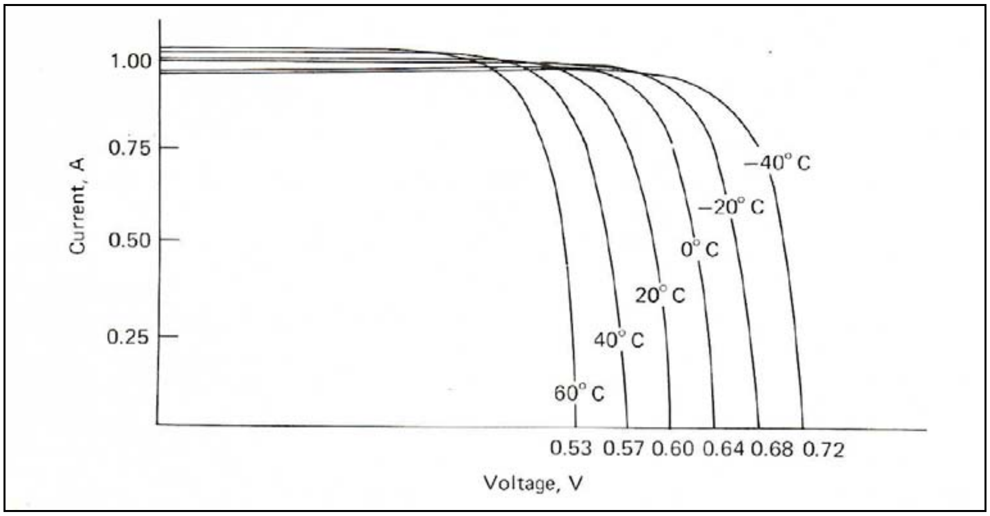

Figure 2.12: V-I Curve vs. Temperature [32]

In order to operate most efficiently, the solar panel should always be operated at the peak power point, which can be accomplished by adding a peak power tracker, see Figure 2.13.

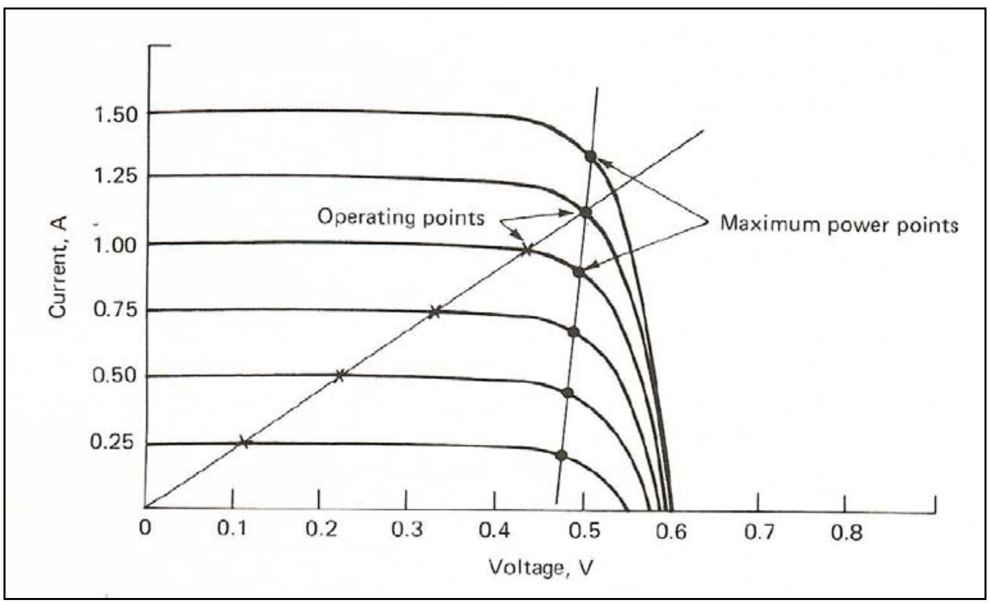

Figure 2.13: Peak Power Tracker [32]

As seen in the previous figures, power output varies depending on many variables; thus the power rating of a panel must be understood in relation to these variables. A graph of daily solar irradiance would show a bell shaped curve which peaks around noon. However, to make energy production estimates easier, power production of a solar system is usually determined based on the number of peak sun hours the site receives, with panels being rated at peak sun hour irradiance. A peak sun hour is defined as "the equivalent number of hours per day when solar irradiance averages 1 kW/m^2" [33]. Basically, to find peak sun hours, one would re-shape the bell curve of hourly solar irradiance into a rectangle with a height of $1kW/m^2$. However, the dispatching algorithm has to operate at frequency higher than once per day, so a means of finding power production based on actual solar irradiance is needed. (For the IDDRR algorithm, temperature effects are ignored).

The actual solar irradiance falling on the Earth's surface at any given time can be divided by the defined solar irradiance of peak sun at $1kW/m^2$. This value may then simply be multiplied by the power rating of the solar panel to find the real-time output of the panel.

SGT 160

The system to be simulated here is based on the SGT 160 solar panel. The SGT 160 is rated at 160 W. Installed prices for three solar systems based on this panel are given below in Figure 2.14. Of most interest might be the 2.2 kW system, since it is close to the Skystream in rated power output.

System Size (KW)	Estimated Annual Power Production Range*	Price w/installation**	Price After Federal Tax Credit of 30%***
1.2	1,575 KWH	$11,200	$7,840
2.2	2,940 KWH	$19,200	$13,440
3.2	4,199 KWH	$27,200	$19,040

* Estimated power production based on PV Watts from NREL
** Sales Tax and Permits Not Included
*** Tax Credit is received after filing taxes

Figure 2.14: Solar Electric Prices [34]

Inverters and Battery Chargers

Inverters are an electrical component used to convert DC power, such as might be generated from solar panels or taken from batteries, into AC power for use in residential electric systems and for connection to the electric grid. Chargers, on the other hand, are used to regulate charging voltage across battery terminals. Chargers and inverters can be purchased both individually, or as a combined system. Typically a system tied to the grid uses only an inverter and a system independent of the grid uses a battery and a charger. However, since the algorithm developed here is dependent on both a grid tie and an ESD system, only inverter-charger combined systems are researched. The characteristics of the charger and inverter, such as efficiency and maximum continuous power ratings, directly affect the inputs of the dispatch algorithm, and special attention is paid to those specifications. Several inverter/charger options are presented further along in Table 2.4.

When sizing an inverter for a renewable energy system, the power rating of the inverter must be large enough to handle the output of the renewable generator. In the case of the Skystream 3.7 and Bergey Excel-S which already have built-in inverters, this parameter can be ignored and the wind turbines can be connected directly to the AC bus of the residence. With a solar system which produces only DC power, however, this rating has to be taken into account. In all systems though, the maximum DC charging current cannot be ignored.

Inverters generally have a high efficiency ranging from 85% to 95% [35], but efficiencies as high as 98.5% [36] and 99.3% [37] have been achieved by some designs. Although no inverter offers the all around best solution for all scenarios, Outback Power and Xantrex are considered to be top-of-the-line [35].

Charger efficiency is typically a bit lower than inverter efficiency, but still fairly high in the mid 80% range and above. However, charger efficiency is not always specified, and it is assumed to be the same as the inverter in that case. Charging schemes vary from simple one-stage chargers to three-stage chargers in which the charge rate changes based on the SOC of the battery in order to increase battery lifespan and efficiency. Since everything must be linearized for this algorithm, staged charging is not enforced. The charging current must simply remain at or below the maximum continuous charge rate.

Table 2.4: Inverter/Charger Options [38]

Name	Efficiency		Power Ratings		Cost
	Inverter	Charger	Overall (W)	Charging (W)	
Outback GTFX2524	91%	n/s (assume 91%)	2500 (24V)	1320	$1,829.99
Outback GVFX3648	92%	n/s (assume 92%)	3600 (48V)	2160	$2,000.74
SMA Sunny Island 5048U	95%	n/s (assume 95%)	5000 (48V)	4800	$5,838.00
Xantrex XW4024	91%	85.8	4000 (24V)	3780	$2,850.00
Xantrex XW6048	92.5%	89.4%	6000 (48V)	5040	$3,495.00

Other Components

In addition to the major components already mentioned, any renewable generator/ESD system contains a number of fuses, breakers and other components needed to wire the whole system together. However, it is not necessary to go into these details as it is assumed that the electrical connectors, breakers, etc are capable of handling the same amount of power seen by the batteries, inverter, etc. A certain percentage of overhead is added to the cost of the major components to account for these additional costs. More specific information on this topic can be found with each case study in the Simulations and Results chapter.

Also, since a new algorithm is controlling all these components, a computer-based power flow control system is needed as well. For the case studies, it is assumed that this system is built into the inverter/charger system, since there is no way to estimate this cost at this time.

CHAPTER 3 - Current DG/ESD Dispatch Methods

As mentioned in Chapter 1, the topic of dispatching methods has not received much academic or industry attention. However, two papers were found relating to this topic and at least one company, GridPoint Inc, provides systems for coordinating DG and ESD systems which can take into account TOD pricing.

Academic Review

Residential Photovoltaic Energy Storage System [39]

A search for literature on the subject of DG and ESD dispatching only turned up two papers, however both of these focused only on solar energy dispatch. The first paper [39], briefly mentioned a dispatching scheme, but it focused more on the development of the hardware that could be used for switching between different operating modes and on the Maximum Peak Power Tracker that the system would be built around. Also, as mentioned previously, the method was designed only for solar-powered systems.

The dispatching schedule used for this system is based on a prescribed load and irradiance schedule and the dispatch itself is be pre-programmed into the system, which allows for little flexibility in optimizing the dispatch as conditions change. The authors stated that “It should be noted that, if the characteristic of any factor is changed, the pattern of daily operation should be redesigned” [39]. Resetting the daily operation of the system would then be up to the owner of the system rather than automated.

While this paper did not offer a dependable means of determining the daily dispatch for customer-owned renewable energy systems with battery storage capabilities, it did propose a reliable system for switching between the different operating modes for solar systems. Therefore, a better dispatching schedule coupled with the system proposed in this paper could be implemented as an effective dispatching system for solar-based systems.

Optimized Dispatch of a Residential Solar Energy System [40]

The second paper reviewed [40] presents an algorithm that is very similar to the IDDRR Algorithm in purpose and closely related in method as well. The authors of this paper sought to create a method of dispatching energy generated by a customer owned solar system with the use of a battery system. Additionally, linear programming is used to solve the dispatch.

The results of this paper showed that a solar panel coupled with an energy storage element and a dispatching scheme could effectively shift customer load and, in some cases, significantly reduce the cost of the customer's energy bill.

While the methods used in this paper were similar to the algorithm developed here, there are also some major differences. First, selling energy back to the grid was not allowed. This is a major facet of the algorithm developed in this research. Selling energy back to the grid allows for better utilization of the renewable generator and can further help the utility to shift or cut peak load if it is done at the proper time. Secondly, inefficiency losses of the energy storage equipment were not included in the dispatching algorithm presented in the paper, which leads to less realistic results. Thirdly, interest rates were not taken into account in the economic evaluation of the systems presented in the paper. Although the authors state this fact, it could lead to some misunderstanding as the payback periods of the system would be greatly reduced. One thing the authors did take into account that is not specifically accounted for in the IDDRR algorithm is the demand charge. A demand charge is based on the peak power demand of a customer in a given month. For instance, if a customer's peak power demand is 10kW and a demand charge of 10 $/kW is included on the customer's bill; a charge of $100 would be included on the electric bill along with energy usage charges. This can be a major contributor to the customer's energy bill, but it is not always included in the customer's rates. The authors could not include the demand charge in the cost function of the LP, but were able to use an iterative method to search through many peak demands coupled with hourly dispatches to find the most economic solution overall.

Industry Review

GridPoint Inc produces systems for monitoring and controlling load while optimizing the use of renewables and battery systems to reduce peak load. Although the algorithms GridPoint systems run on are not available to the public, as these are most likely proprietary, results of how their systems work are available.

In one particular presentation by GridPoint [41], the usefulness of combining solar power systems with batteries and a dispatching scheme was addressed. Figure 3.1 shows how the GridPoint system can be used to shave peak. The load of this residence without a GridPoint system, which is denoted by the blue line, peaks at about 5 kW in hour 16. With a solar array and battery optimized together with the GridPoint system, the load is reduced to 3 kW in hour 16, which is denoted by the teal line. Additionally, the load throughout the peak demand time is also reduced.

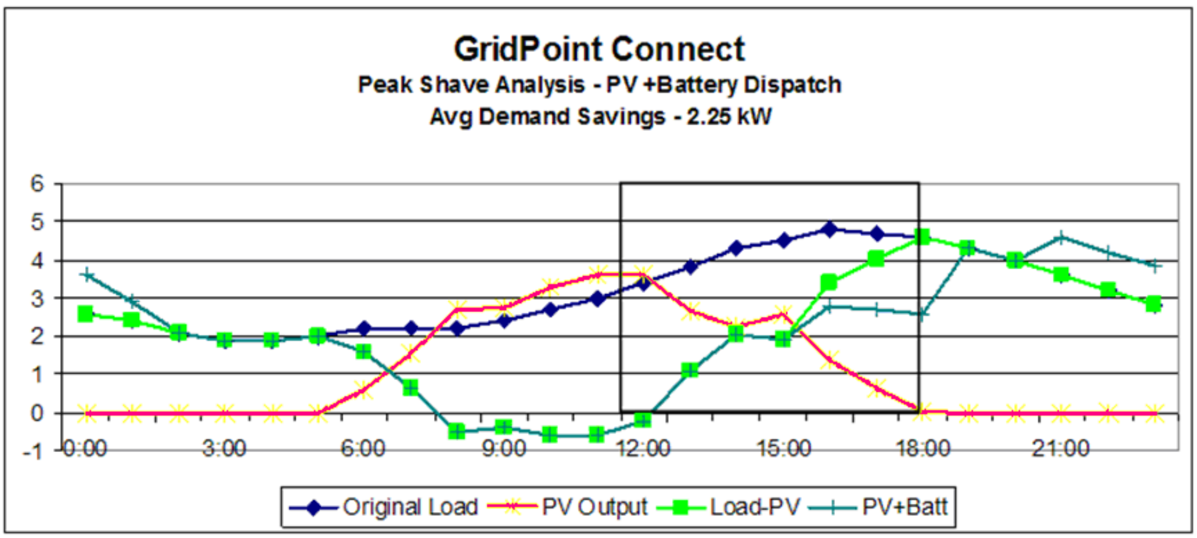

Figure 3.1: GridPoint System for Peak Shaving [41]

GridPoint also offers what look to be some very convenient and effective tools for tracking energy usage to help customers operate their home appliances in the most economic way possible and for providing backup power in the event of an outage. Some of these tools include web applications to track energy usage and cost, which are presented in a very easy to understand way for non-technical people.

CHAPTER 4 - Algorithm Development

A dispatching algorithm, known as the IDDRR algorithm, for customer-owned renewable generation units in a variable pricing market based on Linear Programming (LP) has been developed. The development of this algorithm is explained in detail in the following sections, beginning with the most simplistic version and following through its evolution into a more complicated system, which takes into account many of the non-idealities of a real-world system. Along the way, the shortcomings of each of the developmental versions are explained and the details of how these shortcomings are addressed are offered in the following version. Also, a review of LP and MATLAB is offered to help in the understanding of this development.

A Short Review of Linear Programming and its Implementation in MATLAB

The goal of a LP is to minimize (or maximize) some linear cost function, also referred to as the objective function, relative to a set of linear constraints [54]. The constraints may be either equalities or inequalities. For example, one might want to maximize the sum of x_1 and x_2 relative to the following constraints:

$$
\begin{aligned}
&x_1 + 2x_2 \leq 4 \\
&4x_1 + 2x_2 \leq 12 \\
&-x_1 + x_2 \leq 1 \\
&x_1 \geq 0 \\
&x_2 \geq 0
\end{aligned}
$$

The last two constraints are called the lower bounds (a problem may also include upper bounds) and the remaining constraints are called the inequality constraints (a problem may also include equality constraints). It should be noted that if the problem is not bounded the LP may not converge to a solution.

Figure 4-1 shows this problem solved graphically. The gray area represents the set of feasible solutions relative to the constraints, and the optimal point at which x_1+x_2 is maximized is shown as well. In all bounded LP problems the optimal point falls on one of the corners of the feasible region [54]. While this is a very simple LP problem, as there are only 5 corner points to test, the same properties hold true for any number of variables (dimensions) and constraints so long as every aspect of the problem remains linear. This solution set to this particular problem is $[x_1, x_2] = [8/3, 2/3]$ for a maximum value of $x_1+x_2 = 10/3$.

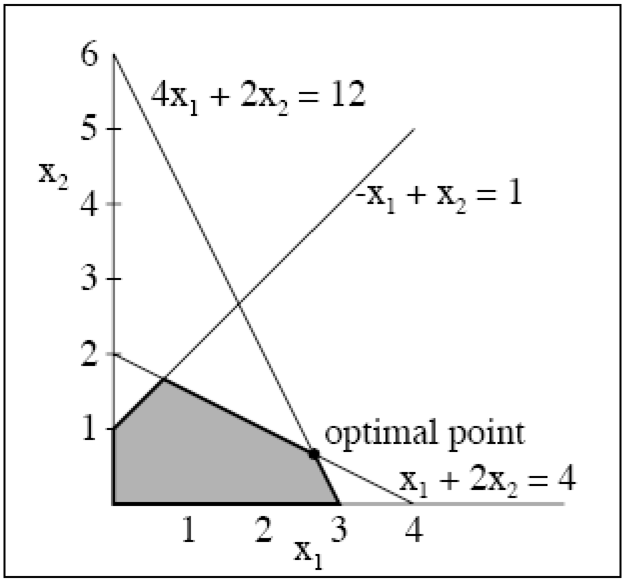

Figure 4.1: Graphical Representation of LP Example [42]

The example shown is easy to solve graphically, but larger LP problems are not. Fortunately, MATLAB has a built in LP function called "*linprog*" for minimizing an objective function. This function can also be used to maximize an objective function by negating the original objective function and finding the point at which the new function is at a minimum (the maximum point of a function is equal to the minimum of that function multiplied by negative one). The example from before would be solved with the MATLAB *linprog* function by defining the coefficients of the objective function and of each of the constraints as follows.

Table 4.1: Objective Function

Mathematical representation	$-x_1 - x_2$
Defined in MATLAB	$x = [x_1 \quad x_2]$ $f = [-1 \quad -1]'$

Table 4.2: Inequality Constraints

Mathematical representation	$x_1 + 2x_2 \le 4$ $4x_1 + 2x_2 \le 12$ $-x_1 + 2x_2 \le 1$
Defined in MATLAB	$A = \begin{bmatrix} 1 & 2 \\ 4 & 2 \\ -1 & 2 \end{bmatrix} \quad b = \begin{bmatrix} 4 \\ 12 \\ 1 \end{bmatrix}$

Table 4.3: Lower Bounds

Mathematical representation	$x_1 \ge 0$ $x_2 \ge 0$
Defined in MATLAB	$lb = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

This problem is solved using the MATLAB syntax shown below. The open brackets are for the equality and upper bound constraints that could be included but are not necessary for this particular problem.

[x] = linprog(f, A, b, [],[],lb,[])

The solution set to this particular problem as found by the MATLAB *linprog* function is [x_1, x_2] = [2.6667, 0.6667], which is exactly what is found using a graphical approach.

Although it is not used in this example, it is often easier to show matrix shorthand notation. A full list of matrix shorthand representations used, along with explanations, is given in at the beginning of this report. These representations are based on MATLAB script as that is the coding language that was used to develop the IDDRR Algorithm and is also the language that will be used for future developments. It should also be pointed out that in the MATLAB programming language matrices can be concatenated, or joined together, by including them together inside a set of brackets. This is not to be confused with matrix multiplication. An example is shown below.

$$\left[\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}\right] = \begin{bmatrix} a_{11} & a_{12} & a_{13} & b_{11} & b_{12} & b_{13} \\ a_{21} & a_{22} & a_{23} & b_{21} & b_{22} & b_{23} \\ a_{31} & a_{32} & a_{33} & b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Also, it is worth mentioning the general convention for writing matrices, as this convention will not be completely followed in this chapter. Usually, variables representing square or rectangular matrices are denoted by uppercase letters, column matrices are denoted by lowercase letters, and the elements of all matrices are represented by the lowercase letter corresponding to the matrices they are contained within along with subscripts to identify their location within the matrix. In this report, the elements of the LP matrices will not correspond to the letter that represents the entire matrix and they will usually not be lowercase. For example, in many of the versions of the LP the column matrix x is defined as $x = [E_P\ E_S\ E_B]'$ rather then $x = [x_1\ x_2\ x_3]'$ or $E = [E_P\ E_S\ E_B]'$. This has been done as a compromise between standard LP and mathematics conventions and what the author believes will be better understood by those in the Power Engineering profession.

Version 1

The first version created is an attempt to generate a dispatch for an ideal system with no inefficiencies. This algorithm must simply find the dispatch that minimizes the cost to the owner of the renewable generation unit while satisfying three basic requirements.

1. all available renewable resources must be used
2. the load must always be satisfied
3. the capacity of the ESD must not be exceeded

Version 1 Linear Program

Decision Variables: R_{pi} = *purchasing rate (cost) in period i*

R_{si} = *selling rate (price) in period i*

E_{Li} = *electrical load in period i*

E_{Ri} = *amount of energy that can be extracted from renewable resources in period i*

E_{BC} = *battery capacity*

Parameters: E_{pi} = *amount of energy purchased in period i*

E_{si} = *amount of energy sold in period i*

E_{Bi} = *energy contained within the battery in time period i*

E_{Bi+1} = *energy contained within the battery in the next time period*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$$

Subject To:
$$\left.\begin{aligned} & E_{Bi} + E_{Pi} - E_{Si} - E_{Bi+1} = E_{Li} - E_{Ri} \\ & E_{Bi} \le E_{BC} \\ & 0 \le E_{Pi} \\ & 0 \le E_{Si} \\ & 0 \le E_{Bi} \end{aligned}\right\} \quad \textit{for } i = 1 \textit{ to } n$$

Where: i = *the period (typically the hour of the day)*

n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Cost Function

The function to minimize, the cost function, is the total price paid for energy over the course of the dispatch period. Therefore, it is the total sum of the cost of purchasing energy in each hour minus the amount of money that is made by selling energy back to the grid in each hour. One of the requirements of the dispatching algorithm is to use all of the available renewable resources. With the cost function defined as it is in Table 4.4, along with the equality constraint defined later, this requirement is always satisfied since that energy source is free.

Table 4.4: Cost Function, Version 1

Mathematical representation	$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$
Defined in MATLAB	$x = [E_P \quad E_S \quad E_B]$ $f = \left[R_{Pi} \quad -R_{Si} \quad zeros(length(E_B))\right]'$

Defining the Constraints

Equality Constraints

The purpose of the equality constraint is to insure that the power flows from each of the sources in the system are balanced. In a real system, the load is supplied by a combination of the renewable resources, energy flows to or from the battery, and the energy flows to or from the grid. Since E_{Bi} is the amount of energy contained within the battery in time period i, E_{Bi} and E_{Bi+1} together show how much is taken from the battery in a single time period

$$E_{Ri} + E_{Bi} + E_{Pi} = E_{Si} + E_{Li} + E_{Bi+1}$$

This equality constraint contains both known and unknown values, as shown in Table 4.5. The set, x, that this algorithm seeks to optimize for a minimum cost includes all the unknowns.

Table 4.5: Dispatch Variables (Version 1)

Known	Unknown
R_{Pi}	E_{Pi}
R_{Si}	E_{Si}
E_{Ri}	E_{Bi}
E_{Li}	E_{Bi+1}

The equality constraints must be of the form $A_{eq}x = b_{eq}$ with the known values in the b_{eq} matrix. Reordering the equation so that the knowns and unknowns are in their proper place gives:

$$E_{Pi} - E_{Si} + E_{Bi} - E_{Bi+1} = E_{Li} - E_{Ri}$$

Table 4.6: Equality Constraints, Version 1

Mathematical representation	$E_{Pi} - E_{Si} + E_{Bi} - E_{Bi+1} = E_{Li} - E_{Ri}, \quad \textit{for i = 1 to n}$
Defined in MATLAB	$Aeq = \left[\begin{bmatrix} \\ eye(n \times n) \\ \\ \end{bmatrix} \begin{bmatrix} \\ -1 \times eye(n \times n) \\ \\ \end{bmatrix} \begin{bmatrix} 1 & -1 & 0 & . & 0 \\ 0 & 1 & -1 & . & 0 \\ . & . & . & & . \\ . & . & & . & -1 \\ 0 & 0 & . & . & 1 \end{bmatrix} \right]$ $beq = \begin{bmatrix} E_{L1} - E_{R1} \\ E_{L2} - E_{R2} \\ . \\ . \\ E_{Ln} - E_{Rn} \end{bmatrix}$

Inequality Constraint

The inequality constraint comes from the battery capacity. At no time can the amount of energy stored in the battery exceed the capacity, $0 \le E_{Bi} \le E_{BC}$. The left side of the equation is satisfied in the lower bounds, but the right hand side of the equation is satisfied as an inequality constraint where $Ax \le b$.

Table 4.7: Inequality Constraints, Version 1

Mathematical representation	$E_{Bi} \leq E_{BC}, \quad \mathit{for\ i = 1\ to\ n}$
Defined in MATLAB	$A = \begin{bmatrix} \begin{bmatrix} zeros(n \times 2n) \end{bmatrix} & \begin{bmatrix} eye(n \times n) \end{bmatrix} \end{bmatrix} \quad b = \begin{bmatrix} E_{BC} \\ E_{BC} \\ . \\ . \\ E_{BC} \end{bmatrix}$

Lower Bounds

It must also be specified that in a feasible dispatch solution, the amount of energy purchased or sold and the amount of energy in the battery cannot be less than zero. This is done in the lower bounds of the LP.

Table 4.8: Lower Bound, Version 1

Mathematical representation	$0 \leq E_{Pi} \quad 0 \leq E_{Si} \quad 0 \leq E_{Bi}, \quad \mathit{for\ i = 1\ to\ n}$
Defined in MATLAB	$lb = \begin{bmatrix} zeros(3n \times 1) \end{bmatrix}$

Version 1 Results

The dispatch algorithm, as it is set up in Version 1, returns an infeasible dispatch. It can quickly be seen by looking at the dispatch plots in Figures 4.2 and 4.3 that in the first hour the load, *El*, is not satisfied correctly, as the difference in the load and available resources, *Er*, which is equal to E_{diff}, is clearly not equal to the amount of energy being purchased from the grid, *Ep*, and the amount of energy coming from the battery, E_B. Also, at the end of the dispatch there is still energy left in the battery and no energy is sold to the grid, E_S. Leaving excess in the battery is clearly not the cheapest solution. The dispatch would immediately become cheaper if this excess were sold back.

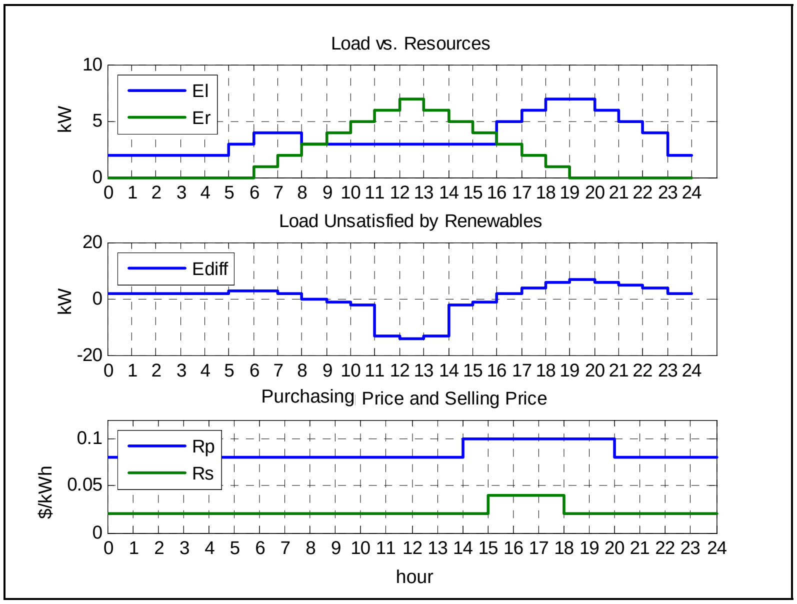

Figure 4.2: Load, Resource, and Rate Plots; Version 1 Example

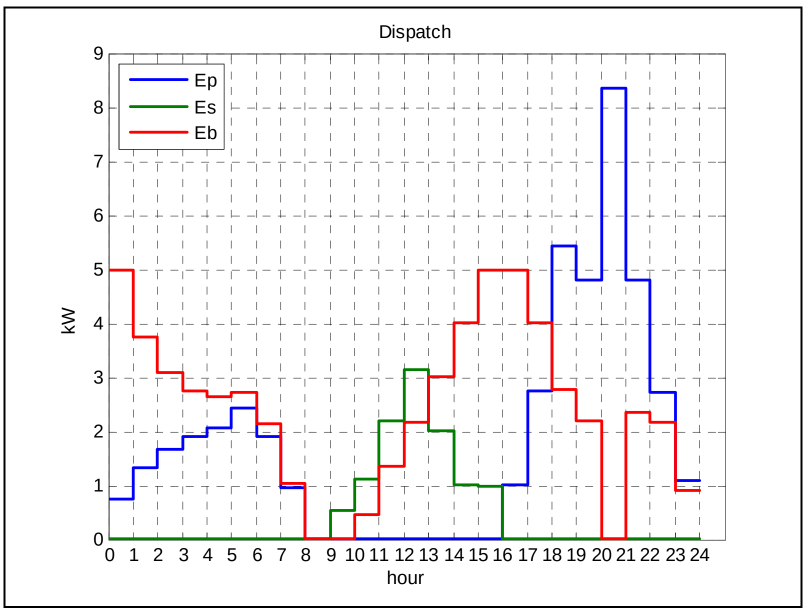

Figure 4.3: Dispatch Schedule; Version 1 Example

The problem is caused by the way E_B has been defined in relation to all the other variables of the objective function and the constraints. All of the energy flow variables E_S, E_P, etc. represent the energy flows to or from those sources, but E_B represents the status, or amount of energy stored in the battery, not the amount of energy flowing to or from the battery.

Version 2

In this version, the battery variable, E_B, is re-defined as the amount of energy flowing to or from the battery, rather than the status of the battery, to coincide with all the other variables in the objective function and the constraints.

Version 2 Linear Program

Decision Variables:
R_{pi} = *purchasing rate (cost) in period i*
R_{si} = *selling rate (price) in period i*
E_{Li} = *electrical load in period i*
E_{Ri} = *amount of energy that can be extracted from renewable resources in period i*
E_{BC} = *battery capacity*

Parameters:
E_{pi} = *amount of energy purchased in period i*
E_{si} = *amount of energy sold in period i*
E_{Bi} = *amount of energy flowing from the battery in time period i (positive → discharging and negative → charging)*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$$

Subject To:
$$\left.\begin{aligned} & E_{Pi} - E_{Si} + E_{Bi} = E_{Li} - E_{Ri} \\ & -\sum_{i=1}^{n}\left(-E_{Bi}\right) \leq 0 \\ & \sum_{i=1}^{n}\left(-E_{Bi}\right) \leq E_{BC} \\ & 0 \leq E_{Pi} \\ & 0 \leq E_{Si} \end{aligned}\right\} \quad \textit{for } i = 1 \textit{ to } n$$

Where:
i = *the period (typically the hour of the day)*
n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Cost Function

The cost function for Version 2 is identical to the cost function for Version 1.

Table 4.9: Cost Function, Version 2

Mathematical representation	$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$
Defined in MATLAB	$x = [E_P \quad E_S \quad E_B]$ $f = [R_{Pi} \quad -R_{Si} \quad zeros(length(E_B))]'$

Defining the Constraints

Equality Constraints

The power flow equation that must be satisfied is shown below.

$$E_{Ri} + E_{Bi} + E_{Pi} = E_{Si} + E_{Li} \qquad where,\ E_B : \begin{matrix} negative \Rightarrow charging \\ positive \Rightarrow discharging \end{matrix}$$

Reorganizing this equation so that all the unknown elements of x are in the A matrix gives the equality constraint, shown in Table 4.10.

Table 4.10: Equality Constraints, Version 2

Mathematical representation	$E_{Pi} - E_{Si} + E_{Bi} = E_{Li} - E_{Ri}, \quad for\ i = 1\ to\ n$
Defined in MATLAB	$Aeq = \left[\left[eye(n \times n) \right] \left[-eye(n \times n) \right] \left[eye(n \times n) \right] \right] \quad beq = \begin{bmatrix} E_{L1} - E_{R1} \\ E_{L2} - E_{R2} \\ . \\ . \\ E_{Ln} - E_{Rn} \end{bmatrix}$

Inequality Constraint

The inequality constraint comes from the physical limitation that the amount of energy stored in the battery must stay between 0 and the maximum battery capacity, E_{BC}.

$$0 \leq battery\ charge \leq E_{BC} \qquad where,\ battery\ charge\ = \sum_{i=1}^{n}\left(-E_{Bi}\right)$$

The negative sign is attached to E_{Bi} in the definition of battery charge because, as previously mentioned, when energy is flowing into the battery to charge it, E_{Bi} is a negative number (E_{Bi} is positive when energy is leaving the battery). Negating the already negative number makes the value positive again so that it may be compared to 0 and E_{BC}, which is always positive.

The battery charging inequality can be split into two separate inequalities as shown below.

$$0 \leq battery\ charge \Rightarrow \ \text{-}battery\ charge \leq 0$$

-and-

$$battery\ charge \leq E_{BC}$$

Table 4.11: Inequality Constraints, Version 2

Mathematical representation	$-\sum_{i=1}^{n}\left(-E_{Bi}\right) \leq 0$ $\sum_{i=1}^{n}\left(-E_{Bi}\right) \leq E_{BC}$
Defined in MATLAB	$A = \begin{bmatrix} \begin{bmatrix} zeros(n \times 2n) \end{bmatrix} & \begin{bmatrix} -tril(ones(n \times n)) \end{bmatrix} \\ \begin{bmatrix} zeros(n \times 2n) \end{bmatrix} & \begin{bmatrix} tril(ones(n \times n)) \end{bmatrix} \end{bmatrix}$ $\quad b = \begin{bmatrix} \begin{bmatrix} E_{BC} \\ E_{BC} \\ . \\ . \\ E_{BC} \end{bmatrix} \\ \begin{bmatrix} 0 \\ 0 \\ . \\ . \\ 0 \end{bmatrix} \end{bmatrix}$

Lower Bound

A lower bound must be specified for the feasible set of solutions to be completely bounded. All variables except for the amount of energy stored in the battery, E_B, should have a lower bound of zero. E_B is already bounded by the inequality constraint and must be allowed to be positive or negative for discharging or charging.

Table 4.12: Lower Bound, Version 2

Mathematical representation	$0 \leq E_{Pi} \quad 0 \leq E_{Si} \quad , \quad \textit{for } i = 1 \textit{ to } n$
Defined in MATLAB	$lb = \begin{bmatrix} \begin{bmatrix} 0 \\ 0 \\ . \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} -\infty \\ -\infty \\ . \\ . \\ -\infty \end{bmatrix} \end{bmatrix}$

Version 2 Results

It can be seen in the Version 2 dispatch graphs that the results from Version 2 are feasible. Figure 4.4 shows the daily load and the resources that are available in each hour of the day as well as the energy rates throughout the day. Figure 4.5 shows the dispatch schedule that has been generated for the day and the status of the battery. All of the constraints are met. The load is satisfied, all renewable resources are used, and the battery capacity is never exceeded. Therefore, Version 2 is a working LP based dispatching algorithm, though it does not account for any real world non-idealities.

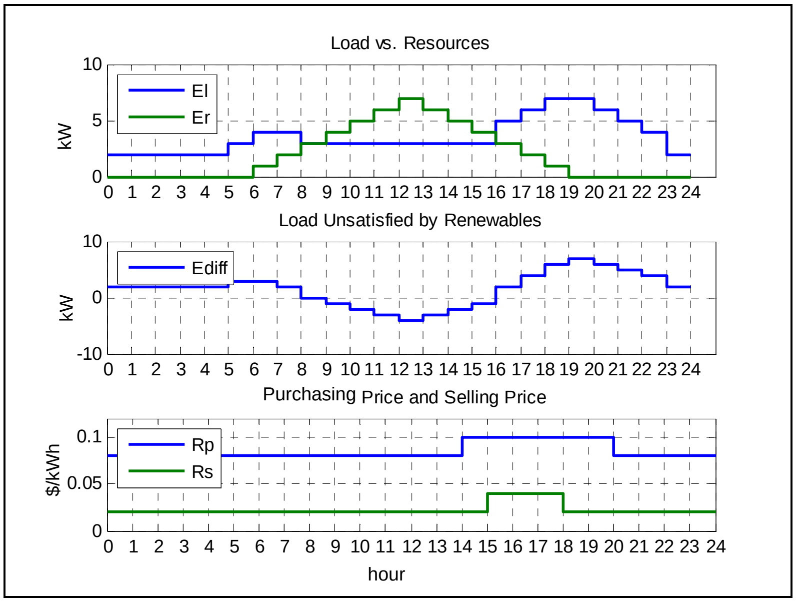

Figure 4.4: Load, Resource, and Rate Plots; Version 2 Example

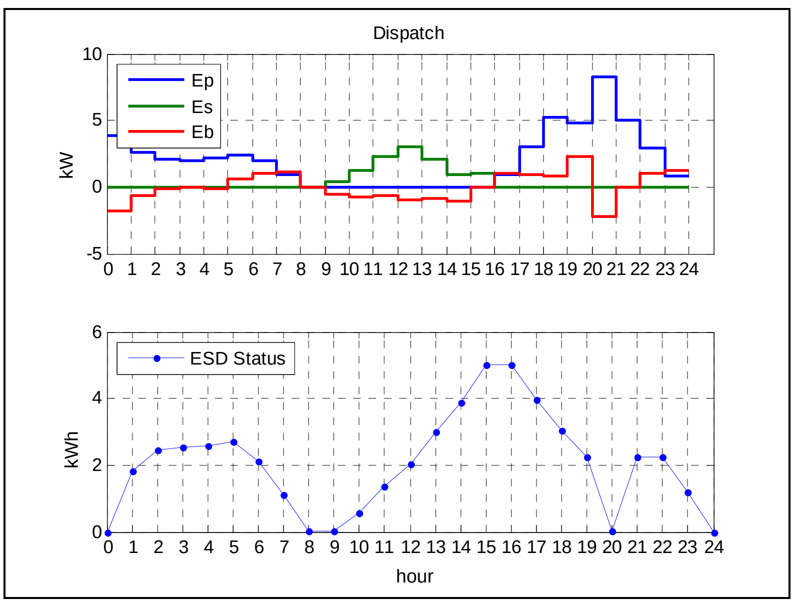

Figure 4.5: Dispatch Schedule; Version 2 Example

Version 2b

In addition to what Version 2 already does, this version takes into account an initial battery charge. If the dispatch is to be updated on a regular time basis, typically once every hour, as more accurate information on the load and renewable resources becomes available, the system will most likely have some amount of energy already stored in the battery. Also, as was already mentioned in Chapter 2, no battery should be totally depleted of stored energy. At the very least, the initial battery charge should be set to the minimum SOC recommended for the battery.

Version 2b Linear Program

Decision Variables: R_{pi} = *purchasing rate (cost) in period i*

R_{si} = *selling rate (price) in period i*

E_{Li} = *electrical load in period i*

E_{Ri} = *amount of energy that can be extracted from renewable resources in period i*

E_{BC} = *battery capacity*

E_{B0} = *initial battery charge*

Parameters: E_{pi} = *amount of energy purchased in period i*

E_{si} = *amount of energy sold in period i*

E_{Bi} = *amount of energy flowing from the battery in time period i (positive → discharging and negative → charging)*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$$

Subject To:
$$\left.\begin{aligned}
&E_{Pi} - E_{Si} + E_{Bi} = E_{Li} - E_{Ri} \\
&-E_{B1} - E_{B2} - \ldots - E_{Bi} \le E_{BC} - E_{B0} \\
&E_{B1} + E_{B2} + \ldots + E_{Bi} \le E_{B0} \\
&0 \le E_{Pi} \\
&0 \le E_{Si}
\end{aligned}\right\} \quad \textit{for } i = 1 \textit{ to } n$$

Where: i = *the period (typically the hour of the day)*

n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Constraints

This is not a very complicated requirement to add and it only affects the inequality constraint. Therefore, redefining the cost function and all the other constraints is not necessary.

In Version 2, the inequality constraint is defined as $0 \le \textit{battery charge} \le E_{BC}$, or

$0 \le -E_{B1} - E_{B2} - \ldots - E_{Bn} \le E_{BC}$.

Adding in the initial battery charge changes the equation to:

$0 \le E_{B0} - E_{B1} - E_{B2} - \ldots - E_{Bi} \le E_{BC}$

Moving what is a known value away from the unknown values in the constraint gives:

$-E_{B0} \le -E_{B1} - E_{B2} - \ldots - E_{Bi} \le E_{BC} - E_{B0}$.

Separating the inequality constraint into two inequality constraints and re-arranging the second into standard LP format gives:

1) $-E_{B1} - E_{B2} - \ldots - E_{Bi} \le E_{BC} - E_{B0}$

2) $-E_{B0} \le -E_{B1} - E_{B2} - \ldots - E_{Bi}$

$E_{B0} \ge E_{B1} + E_{B2} + \ldots + E_{Bi}$

$E_{B1} + E_{B2} + \ldots + E_{Bi} \le E_{B0}$

Table 4.13: Inequality Constraint, Version 2b

Mathematical representation	$-E_{B1} - E_{B2} - \ldots - E_{Bi} \le E_{BC} - E_{B0}, \quad \textit{for } i = 1 \textit{ to } n$ $E_{B1} + E_{B2} + \ldots + E_{Bi} \le E_{B0}, \quad \textit{for } i = 1 \textit{ to } n$
Defined in MATLAB	$A = \begin{bmatrix} \begin{bmatrix} zeros(n \times 2n) \end{bmatrix} & \begin{bmatrix} -tril(ones(n \times n)) \end{bmatrix} \\ \begin{bmatrix} zeros(n \times 2n) \end{bmatrix} & \begin{bmatrix} tril(ones(n \times n)) \end{bmatrix} \end{bmatrix}$ $b = \begin{bmatrix} \begin{bmatrix} E_{BC} - E_{B0} \\ E_{BC} - E_{B0} \\ . \\ . \\ E_{BC} - E_{B0} \end{bmatrix} \\ \begin{bmatrix} E_{B0} \\ E_{B0} \\ . \\ . \\ E_{B0} \end{bmatrix} \end{bmatrix}$

Version 2b Results

Just as in Version 2, this version is satisfying all of the constraints, but it is also capable of handling an initial battery charge. Figure 4.6 shows the load, resources, and energy rates that generate the dispatch schedule shown in 4.7. It can be seen in the dispatch schedule that the ESD initially starts at 1kWh of stored energy. This extra initial energy is used to help satisfy the load in the first 8 hours of the day. By the end of the day, no energy is left in the battery.

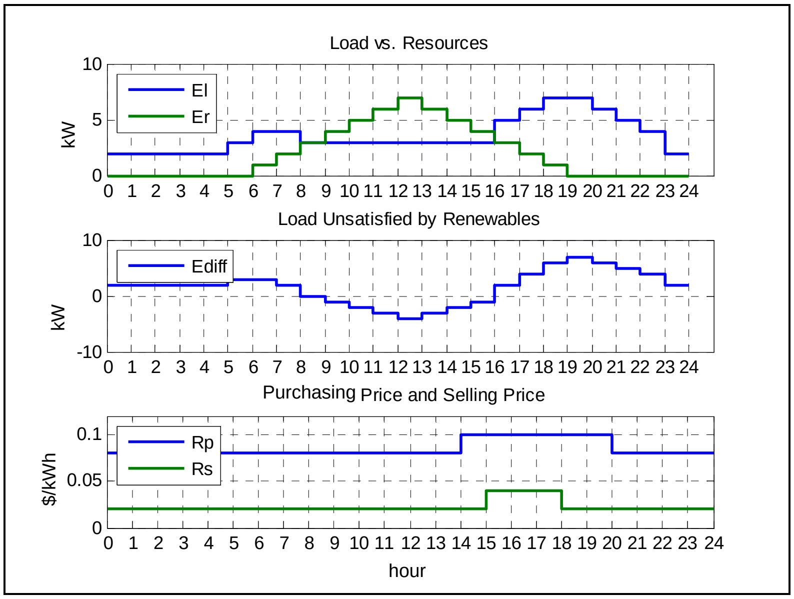

Figure 4.6: Load, Resources, and Rates; Version 2b Example

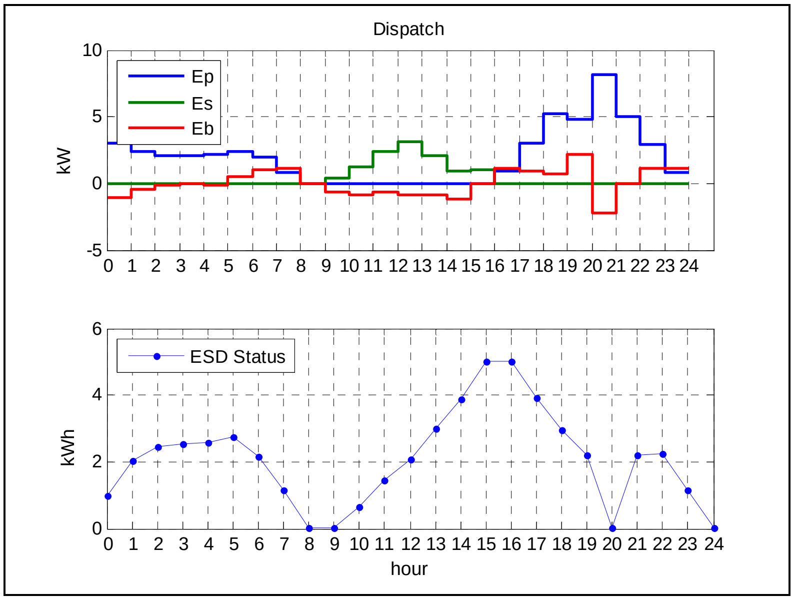

Figure 4.7: Dispatch Schedule; Version 2b Example

Version 2b is a working LP-based dispatching algorithm for an ideal renewable energy system, but it does not take into account any of the non-idealities or inefficiencies of a real system. In the following versions several non-idealities of these types of customer-owned systems are taken into account, including:

1. Number of charge/discharge cycles (lifespan)
2. ESD efficiency
3. Maximum charge/discharge rate (maximum energy flows to or from the battery in one time period)

Version 3

ESD characteristics might vary depending on whether the device is charging or discharging. Therefore, it is useful to redevelop Version 2b so that E_B is re-defined as two separate variables E_{B+} and E_{B-} (E_{B-} for charging and E_{B+} for discharging).

Version 3 Linear Program

Decision Variables:

R_{pi} = *purchasing rate (cost) in period i*

R_{si} = *selling rate (price) in period i*

E_{Li} = *electrical load in period i*

E_{Ri} = *amount of energy that can be extracted from renewable resources in period i*

E_{BC} = *battery capacity*

E_{B0} = *initial battery charge*

Parameters:

E_{pi} = *amount of energy purchased in period i*

E_{si} = *amount of energy sold in period i*

E_{Bi+} = *amount of energy flowing from the battery in time period i (discharging)*

E_{Bi-} = *amount of energy flowing to the battery in time period i (charging)*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$$

$$
\left.
\begin{array}{l}
E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri} \\
-E_{B1-} - E_{B2-} - \ldots - E_{Bi-} - E_{B1+} - E_{B2+} - \ldots - E_{Bi+} \leq E_{BC} - E_{B0} \\
E_{B1-} + E_{B2-} + \ldots + E_{Bi-} + E_{B1+} + E_{B2+} + \ldots + E_{Bi+} \leq E_{B0} \\
E_{Pi} \geq 0 \\
E_{Si} \geq 0 \\
E_{Bi+} \geq 0 \\
E_{Bi-} \leq 0
\end{array}
\right\} \textit{for i = 1 to n}
$$

Subject To: (constraints above)

Where: i = *the period (typically the hour of the day)*

n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Cost Function

The cost function is still the same mathematically since there is no cost associated with charging or discharging, but the parameters are redefined in MATLAB as shown in Table 4.14.

Table 4.14: Cost Function, Version 3

Mathematical representation	$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$
Defined in MATLAB	$x = [E_P \quad E_S \quad E_{B+} \quad E_{B-}]$ $f = \left[R_{Pi} \quad -R_{Si} \quad zeros(1 \times 2n)\right]'$

Defining the Constraints

Equality Constraints

Previously the equality constraint was defined as $E_{Ri} + E_{Bi} + E_{Pi} = E_{Si} + E_{Li}$. With E_B now being separated into two variables the equality constraint becomes

$$E_{Ri} + E_{Bi+} + E_{Bi-} + E_{Pi} = E_{Si} + E_{Li} \;\Rightarrow\; E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} + E_{Ri}$$

Table 4.15: Equality Constraints, Version 3

Mathematical representation	$E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri}$, *for i = 1 to n*
Defined in MATLAB	$Aeq = \begin{bmatrix} \begin{bmatrix} eye(n \times n) \end{bmatrix} & \begin{bmatrix} -eye(n \times n) \end{bmatrix} & \begin{bmatrix} eye(n \times n) \end{bmatrix} & \begin{bmatrix} eye(n \times n) \end{bmatrix} \end{bmatrix}$ $beq = \begin{bmatrix} E_{L1} - E_{R1} \\ E_{L2} - E_{R2} \\ . \\ . \\ E_{Ln} - E_{Rn} \end{bmatrix}$

Inequality Constraints

The inequality constraints are re-defined from the previous version as follows:

1)
$$-E_{B1}-E_{B2}-\ldots-E_{Bi}\le E_{BC}-E_{B0}$$
$$\Downarrow$$
$$-E_{B1-}-E_{B2-}-\ldots-E_{Bi-}-E_{B1+}-E_{B2+}-\ldots-E_{Bi+}\le E_{BC}-E_{B0}$$

2)
$$E_{B1}+E_{B2}+\ldots+E_{Bi}\le E_{B0}$$
$$\Downarrow$$
$$E_{B1-}+E_{B2-}+\ldots+E_{Bi-}+E_{B1+}+E_{B2+}+\ldots+E_{Bi+}\le E_{B0}$$

Table 4.16: Inequality Constraint, Version 3

Mathematical representation	$-E_{B1-}-E_{B2-}-\ldots-E_{Bi-}-E_{B1+}-E_{B2+}-\ldots-E_{Bi+}\le E_{BC}-E_{B0}$, *for i = 1 to n* $E_{B1-}+E_{B2-}+\ldots+E_{Bi-}+E_{B1+}+E_{B2+}+\ldots+E_{Bi+}\le E_{B0}$, *for i = 1 to n*
Defined in MATLAB	$A=\begin{bmatrix}\begin{bmatrix} zeros(n\times 2n)\end{bmatrix} & \begin{bmatrix}-tril(ones(n\times n))\end{bmatrix} & \begin{bmatrix}-tril(ones(n\times n))\end{bmatrix}\\ \begin{bmatrix} zeros(n\times 2n)\end{bmatrix} & \begin{bmatrix}tril(ones(n\times n))\end{bmatrix} & \begin{bmatrix}tril(ones(n\times n))\end{bmatrix}\end{bmatrix}$ $b=\begin{bmatrix}\begin{bmatrix}C-E_{BC}\\ C-E_{BC}\\ .\\ .\\ C-E_{BC}\end{bmatrix}\\ \begin{bmatrix}E_{B0}\\ E_{B0}\\ .\\ .\\ E_{B0}\end{bmatrix}\end{bmatrix}$

Lower and Upper Bounds

This is the first version to include an upper bound. Since E_{B-} is always less than or equal to zero, it needs an upper bound of zero. E_{B+}, likewise, has a lower bound of zero.

Table 4.17: Upper and Lower Bounds, Version 3

Mathematical representation	$E_{Pi} \geq 0$ $E_{Si} \geq 0$ $E_{Bi+} \geq 0$ $E_{Bi-} \leq 0$
Defined in MATLAB	$lb = \begin{bmatrix} \begin{bmatrix} 0 \\ . \\ . \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} -\infty \\ . \\ -\infty \end{bmatrix} \\ \\ \end{bmatrix} \quad ub = \begin{bmatrix} \begin{bmatrix} \infty \\ . \\ . \\ . \\ \infty \end{bmatrix} \\ \begin{bmatrix} \infty \\ . \\ \infty \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \\ \\ \end{bmatrix}$

Version 3 Results

The purpose of this version is to separate the variables for charging and discharging in the dispatching algorithm. Figure 4.9 shows the dispatch resulting from the inputs given in Figure 4.8. These are the same inputs tested on the previous version including the initial ESD charge of 1 kWh. This version has been successful as the dispatch shown in Figure 4.9 is identical to the dispatch computed by Version 2b. This version may have one flaw, though. E_{B-} and E_{B+} are both non-zero values in each hour. Since charging and discharging cannot occur in the same hour, it should be expected that one of these variables should always be zero.

However, combining the two variables back together as $E_B = E_{B+} + E_{B-}$ does give the valid dispatch shown in Figure 4.9.

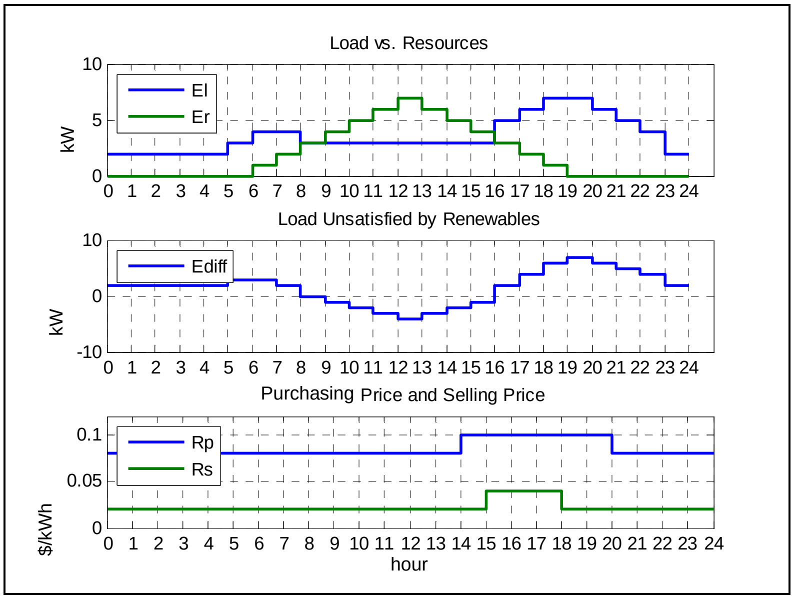

Figure 4.8: Load, Resources, and Rates; Version 3 Example

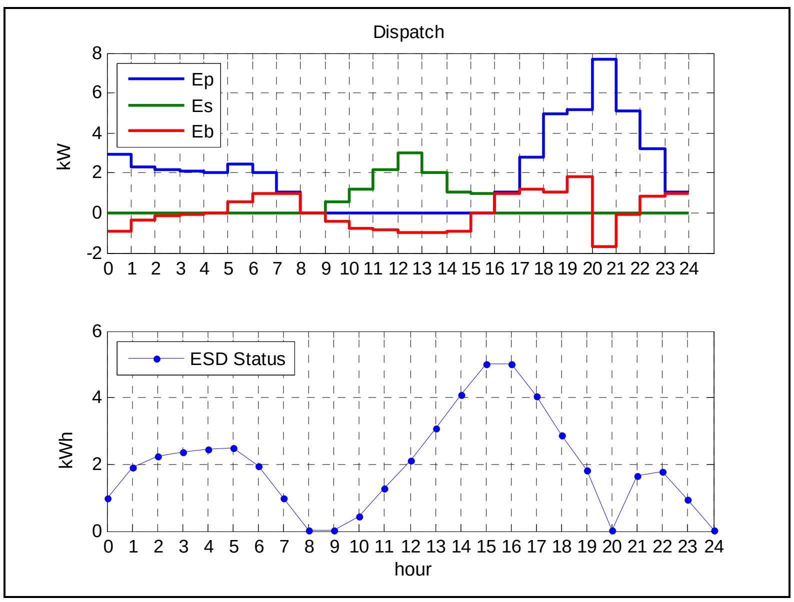

Figure 4.9: Dispatch Schedule; Version 3 Example

Version 3.1

All versions of the dispatching algorithm previous to this one have not included the non-idealities, such as efficiencies and physical limitations, of a real world system. The next version includes the non-idealities that most affect a real world system using 24 hour dispatches. These non-idealities are listed as follows:

1. ESD (battery) cycle life (the number of charge/discharge cycles)
2. charging/discharging efficiency of the ESD system
3. ESD maximum discharge/charge rate
4. minimum discharge level

It should also be reemphasized that although self discharge is a reality of lead-acid batteries, it is not taken into account as part of the dispatching algorithm because it's such a small number (1% to 3% per month) that it does not effect a battery that is being cycled roughly once per day.

Version 3.1 Linear Program

Decision Variables:

R_{pi} = *purchasing rate (cost) in period i*

R_{si} = *selling rate (price) in period i*

R_B = *cycling cost coefficient*

E_{Li} = *electrical load in period i*

E_{Ri} = *amount of energy that can be extracted from renewable resources in period i*

E_{B0} = *initial battery charge*

E_{BCmin} = *minimum battery capacity*

E_{BCmax} = *maximum battery capacity*

E_{Bdis_max} = *maximum hourly, or other period, discharge*

E_{Bdis_min} = *maximum hourly, or other period, charge*

e_{dis} = *ESD discharging efficiency*

e_{char} = *ESD charging efficiency*

Parameters: E_{pi} = *amount of energy purchased in period i*

E_{si} = *amount of energy sold in period i*

E_{Bi+} = *amount of energy flowing from the battery in time period i (discharging)*

E_{Bi-} = *amount of energy flowing to the battery in time period i (charging)*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i}$$

Subject To:

$$\left.\begin{aligned}
&E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri} \\
&e_{dis} \times (-E_{B1-} - E_{B2-} - \ldots - E_{Bi-}) + \ldots \\
&\ldots + e_{char} \times (-E_{B1+} - E_{B2+} - \ldots - E_{Bi+}) \le E_{BC\max} - E_{B0} \\
&e_{dis} \times (E_{B1-} + E_{B2-} + \ldots + E_{Bi-}) + \ldots \\
&\ldots + e_{char} \times (+E_{B1+} + E_{B2+} + \ldots + E_{Bi+}) \le E_{B0} - E_{BC\min} \\
&0 \le E_{Bi+} \le E_{Bdis_\max} \\
&E_{Bchar_\max} \le E_{Bi-} \le 0
\end{aligned}\right\} \textit{for } i = 1 \textit{ to } n$$

Where: i = *the period (typically the hour of the day)*

n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Cost Function (ESD Lifespan)

Lifespan can be accounted for in the cost function. A cycle (full charge and full discharge) has a cost associated with it. This cost is the total cost of the battery system divided by the lifespan (in cycles), although this does not take into account the depreciation of the battery, which does not last forever even if it is not cycled, but that would not be possible to implement on an LP-based daily dispatching algorithm.

Cycle cost = (cost of the ESD system) / (cycle life)

By including this in the cost function, the LP dispatching algorithm optimizes the number of ESD cycles in a single dispatch to find the best balance between maximizing the lifespan of the ESD and utilizing the system effectively to reduce the cost of the customer's daily energy usage.

Since a full charge or discharge does not occur in every hour, a means of determining the cost of a partial cycle is needed. The cost in each hour is the cycle cost times the percentage of the cycle that is completed.

$$\textit{hourly cost of cycling} \quad = \textit{(cycle cost)} \times \left(\frac{E_{Bi}}{E_{BC}} \right) \times \frac{1}{2}$$

$$= E_{Bi} \times R_B \qquad \textit{where, } R_B = \textit{(cycle cost)} \times \left(\frac{1}{2E_{BC}} \right)$$

The cycle cost is multiplied by the fraction of charge or discharge that occurs in the time period and then multiplied by ½ because the ESD is only charging or discharging in a given hour, not both (a full cycle includes both a full charge and discharge). Also, it should be noted that although E_B could be positive or negative, the absolute value of E_B is not needed because there are separate variables for charging and discharging. The signage is taken into account separately for these variables in the cost function.

Table 4.18: Cost Function, Version 3.1

Mathematical representation	$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i}$
Defined in MATLAB	$x = [E_P \quad E_S \quad E_{B+} \quad E_{B-}]$ $f = \left[R_{Pi} \quad -R_{Si} \quad R_B \quad -R_B \right]'$

Also, it should be noted that the actual cost of energy is only the first two terms of the cost equation, but the LP seeks to minimize the sum of all the terms to find the best possible dispatch.

Defining the Constraints

Equality Constraints

This version uses the same equality constraints as the previous version, which makes sense because the power flow balance must still be satisfied. The efficiencies are accounted for in the inequality constraint, which keeps track of the amount of energy stored in the ESD, although an alternative approach would be to account for them here as well.

Table 4.19: Equality Constraint, Version 3.1

Mathematical representation	$E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri}$, *for i = 1 to n*
Defined in MATLAB	$Aeq = \left[\left[\; eye(n \times n) \; \right] \left[\; -eye(n \times n) \; \right] \left[\; eye(n \times n) \; \right] \left[\; eye(n \times n) \; \right] \right]$ $beq = \begin{bmatrix} E_{L1} - E_{R1} \\ E_{L2} - E_{R2} \\ . \\ . \\ E_{Ln} - E_{Rn} \end{bmatrix}$

Inequality Constraints (Charging/Discharging Efficiencies and Minimum Discharge Level)

Charging/Discharging Efficiencies

The variable E_B represents the amount that is taken out or put into the battery, but the actual amount that gets out or in depends on the efficiency of the ESD. Therefore, these numbers need to be multiplied by some efficiency coefficient, e.

e_{dis} for ESD discharging

e_{char} for ESD charging

Which changes the A matrix of the inequality constraint as is shown in the Table 4.20.

Table 4.20: Inequality Constraint (*A* Matrix Only), Version 3.1

Mathematical representation	$e_{dis} \times (-E_{B1-} - E_{B2-} - ... - E_{Bi-}) + e_{char} \times (-E_{B1+} - E_{B2+} - ... - E_{Bi+}) \le E_{BC} - E_{B0}$, *for i = 1 to n* $e_{dis} \times (E_{B1-} + E_{B2-} + ... + E_{Bi-}) + e_{char} \times (+E_{B1+} + E_{B2+} + ... + E_{Bi+}) \le E_{B0}$, *for i = 1 to n*
Defined in MATLAB	$A = \begin{bmatrix} [zeros(n \times 2n)] & [-e_{dis} \times tril(ones(n \times n))] & [-e_{char} \times tril(ones(n \times n))] \\ [zeros(n \times 2n)] & [e_{dis} \times tril(ones(n \times n))] & [e_{char} \times tril(ones(n \times n))] \end{bmatrix}$

Minimum Discharge Level

It may be impossible, or generally a bad idea to deplete some types of ESDs to zero charge. Therefore, constraints are put on how low the ESD can be discharged. Previously, it was stated that the battery had to remain between 0 and E_{BC}.

$$0 \leq battery\ charge \leq E_{BC}$$

That is now redefined as:

$$E_{BC\min} \leq battery\ charge \leq E_{BC\max}$$

The updated constraint is shown in the Table 4.21 along with the updates that were made to the A matrix of the constraint previously due to charging and discharging efficiencies.

Table 4.21: Inequality Constraint, Version 3.1

Mathematical representation	$e_{dis} \times (-E_{B1-} - E_{B2-} - ... - E_{Bi-}) + e_{char} \times (-E_{B1+} - E_{B2+} - ... - E_{Bi+}) \leq E_{BC\max} - E_{B0}$, *for i = 1 to n* $e_{dis} \times (E_{B1-} + E_{B2-} + ... + E_{Bi-}) + e_{char} \times (+E_{B1+} + E_{B2+} + ... + E_{Bi+}) \leq E_{B0} - E_{BC\min}$, *for i = 1 to n*
Defined in MATLAB	$A = \begin{bmatrix} \begin{bmatrix} zeros(n \times 2n) \end{bmatrix} & \begin{bmatrix} -e_{dis} \times tril(ones(n \times n)) \end{bmatrix} & \begin{bmatrix} -e_{char} \times tril(ones(n \times n)) \end{bmatrix} \\ \begin{bmatrix} zeros(n \times 2n) \end{bmatrix} & \begin{bmatrix} e_{dis} \times tril(ones(n \times n)) \end{bmatrix} & \begin{bmatrix} e_{char} \times tril(ones(n \times n)) \end{bmatrix} \end{bmatrix}$ $b = \begin{bmatrix} \begin{bmatrix} E_{BC\max} - E_{B0} \\ E_{BC\max} - E_{B0} \\ . \\ . \\ E_{BC\max} - E_{B0} \end{bmatrix} \\ \begin{bmatrix} E_{B0} - E_{BC\min} \\ E_{B0} - E_{BC\min} \\ . \\ . \\ E_{B0} - E_{BC\min} \end{bmatrix} \end{bmatrix}$

Upper and Lower Bound (Maximum Charging / Discharging Rates)

The most that can be taken out of or put into the ESD in a given hour is already constrained by what is available in the battery, or the battery's current charge state, via the inequality constraint applied in matrices *A* and *b*. However, it should be further constrained by the maximum charge/discharge that can physically occur in a single time period without damaging the battery. These constraints can be placed in the upper and lower bounds.

Table 4.22: Upper and Lower Bounds, Version 3.1

Mathematical representation	$0 \le E_{Bi+} \le E_{Bdis\_\max}$, *for i = 1 to n* $E_{Bchar\_\max} \le E_{Bi-} \le 0$, *for i = 1 to n*
Defined in MATLAB	$lb = \begin{bmatrix} \begin{bmatrix} 0 \\ . \\ . \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} -E_{Bchar\_\max} \\ . \\ -E_{Bchar\_\max} \end{bmatrix} \end{bmatrix}$ $ub = \begin{bmatrix} \begin{bmatrix} \infty \\ . \\ . \\ . \\ \infty \end{bmatrix} \\ \begin{bmatrix} E_{Bdis\_\max} \\ . \\ E_{Bdis\_\max} \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \end{bmatrix}$

Also, it is important to note where the maximum hourly charge/discharge is defined, i.e. before or after losses in efficiency. For example, if the most that can be put into the battery is 1.25 kW, defined at point *P1* in Figure 4.10, the amount that would make it into the battery is actually only 1.125 kW (with an efficiency of 90%). On the other hand, if the most that can be put in is 1.25 kW defined at point *P2*, then 1.39 kW would have to be sent to the battery (1.25/0.9).

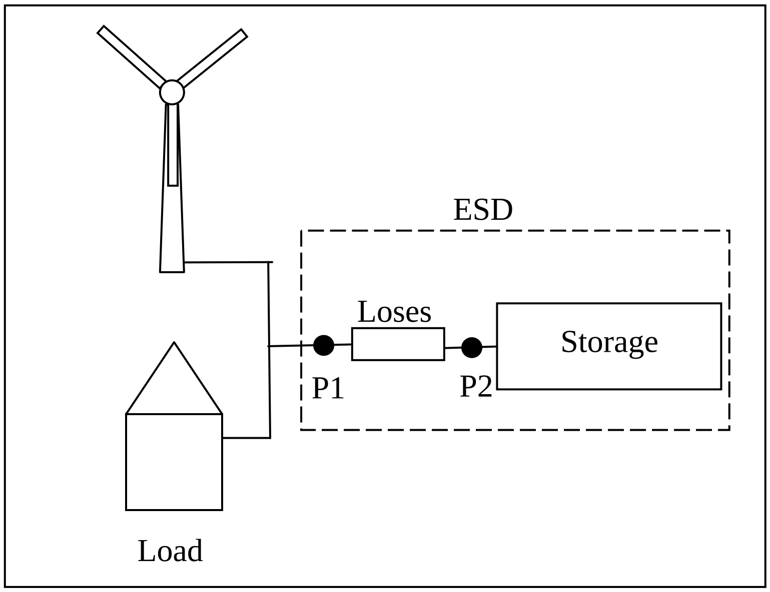

Figure 4.10: Point of System Losses

Either point works, but it seems more intuitive to define the maximum hourly charging/discharging as being at point *P1*; however this has to be kept in mind when specifying the characteristics of the ESD.

Version 3.1 Results

Version 3.1 is tested with the constraints shown in Table 4.23. Although the constraints chosen are not based on any real battery, the numbers are close to the constraints a realistic system would have. The results of this test are shown in Figures 4.11 and 4.12

Table 4.23: System Constraints, Version 3.1 Example

Maximum ESD Capacity (kWh)	5
Minimum Discharge Level (kWh)	0.5
Maximum Charging per Hour (kWh)	1.25
Maximum Discharging per Hour (kWh)	1.25
Charging Efficiency (%)	90
Discharging Efficiency (%)	90
Cycling Cost ($/cycle)	.04

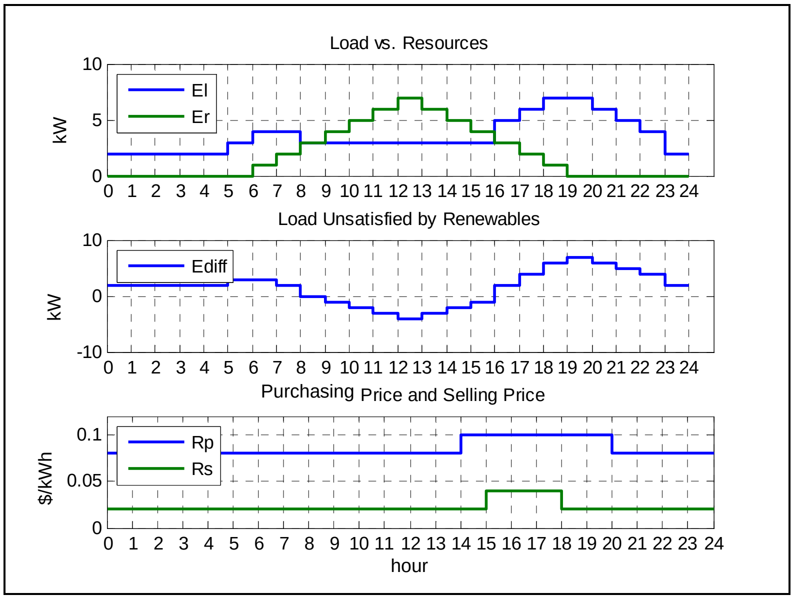

Figure 4.11: Load Resources, and Rates; Version 3.1 Example

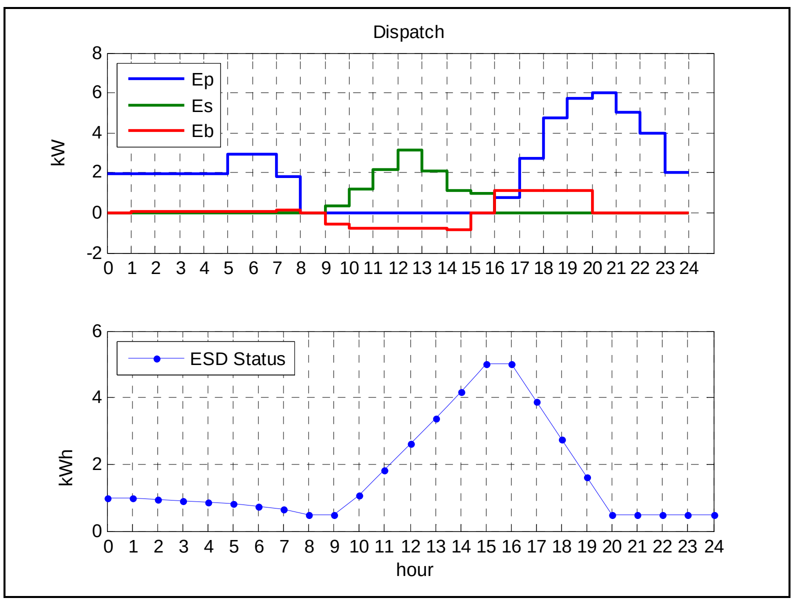

Figure 4.12: Dispatch Schedule; Version 3.1 Example

Although the load, resources, and rates are the same as the system that was tested on Version 3, the dispatch generated by Version 3.1 is dramatically different. These differences can be attributed to the constraints put on the system in Version 3.1. The constraint that appears to have the most effect is the hourly maximum charging and discharging limits. Between the 17th and 20th hours, the system is discharging at its maximum limit of 1.25 kW and supplies the load with 1.125 kW of power (1.25 kW × 0.9 = 1.125 kW). Also, it can be seen in Figure 4.12 that the system always keeps the battery at or above the minimum discharge level, which in this case is 0.5 kWh.

Version 3.1 has satisfied the requirements it intended to; however another problem was discovered, which also would afflict all the previous versions. When given a rate case where the selling rate is higher than the buying rate at any time, an unbounded error occurs. In the next version, a means to correct this error is presented.

Version 4

Several versions of the dispatching algorithm have been developed prior to this version, the most advanced of which can compute a dispatch while taking into account the major non-idealities of a realistic system. However, these previous versions encounter an unbounded error any time the selling price of energy is higher than the buying price. This is because the system tries to sell (and buy to satisfy the equality constraint) enormous amounts of energy in order to make the most money. The root cause of this problem is the first part of the cost equation.

$$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si}$$

When cost is equated like that, it makes sense to buy excess energy just to sell it back in the same time period if the selling price is higher than the buying price. In the real world though, the hourly cost of energy is based on the net amount of energy usage in that hour multiplied by the appropriate rate.

$$Cost = \sum_{i=1}^{n} (E_{pi} + E_{si}) \times R$$

Unfortunately, this cost equation cannot be implemented in an LP because the LP would somehow have to know what rate to use in advance. Some attempts were made at using the real cost equation with some tricks to determine the rate based on whether E_P - E_S is positive or negative, but these attempts resulted in a non-linear constraint.

To fix this problem a dummy variable is added to the cost equation that makes it unprofitable to buy and sell huge amounts of energy at the same time. The strategy is simple; the dummy variable grows faster than the profit that would be made by buying and selling huge amounts of energy at the same time in hours when the selling price is higher than the purchasing price.

Version 4 Linear Program

Decision Variables:

Decision Variables:	R_{pi}	=	*purchasing rate (cost) in period i*
	R_{si}	=	*selling rate (price) in period i*
	R_B	=	*cycling cost coefficient*
	E_{Li}	=	*electrical load in period i*
	E_{Ri}	=	*amount of energy that can be extracted from renewable resources in period i*
	E_{B0}	=	*initial battery charge*
	E_{BCmin}	=	*minimum battery capacity*
	E_{BCmax}	=	*maximum battery capacity*
	E_{Bdis_max}	=	*maximum hourly, or other period, discharge*
	E_{Bdis_min}	=	*maximum hourly, or other period, charge*
	e_{dis}	=	*ESD discharging efficiency*
	e_{char}	=	*ESD charging efficiency*
	c_i	=	*dummy variable coefficient*

$$\textit{where, } c = \begin{Bmatrix} 0, & R_P \geq R_S \\ R_S \times m, & R_S \leq R_P \end{Bmatrix}$$

and $m = 1.0001$

Parameters:	E_{pi}	=	*amount of energy purchased in period i*
	E_{si}	=	*amount of energy sold in period i*
	E_{Bi+}	=	*amount of energy flowing from the battery in time period i (discharging)*
	E_{Bi-}	=	*amount of energy flowing to the battery in time period i (charging)*
	d	=	*dummy variable*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i} + \sum_{i=1}^{n} d_i \times c_i$$

$$
\text{Subject To:}\quad \left.\begin{aligned}
&E_{Pi} - E_{Si+} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri} \\
&d_i - E_{Si} = 0 \\
\\
&e_{dis} \times (-E_{B1-} - E_{B2-} - \ldots - E_{Bi-}) + \ldots \\
&\ldots + e_{char} \times (-E_{B1+} - E_{B2+} - \ldots - E_{Bi+}) \le E_{BC\max} - E_{B0} \\
\\
&e_{dis} \times (E_{B1-} + E_{B2-} + \ldots + E_{Bi-}) + \ldots \\
&\ldots + e_{char} \times (+E_{B1+} + E_{B2+} + \ldots + E_{Bi+}) \le E_{B0} - E_{BC\min} \\
\\
&0 \le E_{Bi+} \le E_{Bdis\_\max} \\
&E_{Bchar\_\max} \le E_{Bi-} \le 0 \\
&d_i \ge 0
\end{aligned}\right\}\ \textit{for } i = 1 \textit{ to } n
$$

Where: i = *the period (typically the hour of the day)*

n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Cost

The dummy variable '*d*' has a cost coefficient '*c*' associated with it. Since there is not a problem when the purchasing price is higher than the selling price, *c* is set to 0 in all those hours. However, when the selling price is higher than the buying price, *c* should be slightly higher than the selling rate, R_S, such as 1.0001(R_S) so that it grows faster than the profit made by buying and selling huge amounts of energy in the same hour. This number should be kept as small as possible though, because if it were too large it would begin to affect legitimate cases where excess is bought to store in the ESD for later use.

Trial and error with MATLAB confirmed that a 'c' value of 1.0001 works best, since it is the smallest number that can be used. Apparently, a value less than 1.0001 is too close to 1 and does not fix the problem. Other numbers may be better suited to other coding languages.

Table 4.24: Cost Function, Version 4

Mathematical representation	$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i} + \sum_{i=1}^{n} d_i \times c_i$
Defined in MATLAB	$x = [E_P \quad E_S \quad E_{B+} \quad E_{B-} \quad d]$ $f = [R_{Pi} \quad -R_{Si} \quad R_B \quad -R_B \quad c]'$ $where,\ c = \begin{Bmatrix} 0, & R_P \geq R_S \\ R_S \times m, & R_S \leq R_P \end{Bmatrix}$ $and\ m = 1.0001$

Defining the Constraints

Equality Constraints

The dummy variable must grow along with the energy that is sold back to the utility, $d = E_S$. This is added into the equality constraint.

Table 4.25: Equality Constrain, Version 4

Mathematical representation	$E_{Pi} - E_{Si+} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri}, \quad for\ i = 1\ to\ n$ $d_i - E_{Si} = 0, \quad for\ i = 1\ to\ n$
Defined in MATLAB	$Aeq = \begin{bmatrix} [eye(n \times n)] & [-eye(n \times n)] & [eye(n \times n)] & [eye(n \times n)] & [zeros(n \times n)] \\ [zeros(n \times n)] & [-eye(n \times n)] & [zeros(n \times n)] & [zeros(n \times n)] & [eye(n \times n)] \end{bmatrix}$ $beq = \begin{bmatrix} \begin{bmatrix} E_{L1} - E_{R1} \\ E_{L2} - E_{R2} \\ . \\ . \\ E_{Ln} - E_{Rn} \end{bmatrix} \\ \begin{bmatrix} 0 \\ 0 \\ . \\ . \\ 0 \end{bmatrix} \end{bmatrix}$

Inequality Constraints

Mathematically, the inequality constraints does not change from the previous version, but the A matrix must be updated to show that the new variables have no bearing on the constraint.

Table 4.26: Inequality Constraint, Version 4

Mathematical representation	$e_{dis}\times(-E_{B1-}-E_{B2-}-...-E_{Bi-})+e_{char}\times(-E_{B1+}-E_{B2+}-...-E_{Bi+})\le E_{BC\max}-E_{B0}$, *for i = 1 to n* $e_{dis}\times(E_{B1-}+E_{B2-}+...+E_{Bi-})+e_{char}\times(+E_{B1+}+E_{B2+}+...+E_{Bi+})\le E_{B0}-E_{BC\min}$, *for i = 1 to n*
Defined in MATLAB	$A=\begin{bmatrix}[zeros(n\times 2n)] & [-e_{dis}\times tril(ones(n\times n))] & [-e_{char}\times tril(ones(n\times n))] & [zeros(n\times n)]\\ [zeros(n\times 2n)] & [e_{dis}\times tril(ones(n\times n))] & [-e_{char}\times tril(ones(n\times n))] & [zeros(n\times n)]\end{bmatrix}$ $b=\begin{bmatrix}\begin{bmatrix}E_{BC\max}-E_{B0}\\ E_{BC\max}-E_{B0}\\ .\\ .\\ E_{BC\max}-E_{B0}\end{bmatrix}\\ \begin{bmatrix}E_{B0}-E_{BC\min}\\ E_{B0}-E_{BC\min}\\ .\\ .\\ E_{B0}-E_{BC\min}\end{bmatrix}\end{bmatrix}$

Upper and Lower Bounds

The dummy variable, *d*, should always be greater than zero and this must be included in the lower bounds.

Mathematical representation	$0 \le E_{Bi+} \le E_{Bdis\_\max}$, *for i = 1 to n* $E_{Bchar\_\max} \le E_{Bi-} \le 0$, *for i = 1 to n* $d_i \ge 0$, *for i = 1 to n*
Defined in MATLAB	$lb = \begin{bmatrix} \begin{bmatrix} 0 \\ . \\ . \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} -E_{Bchar\_\max} \\ . \\ -E_{Bchar\_\max} \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \end{bmatrix}$ $ub = \begin{bmatrix} \begin{bmatrix} \infty \\ . \\ . \\ . \\ \infty \end{bmatrix} \\ \begin{bmatrix} E_{Bdis\_\max} \\ . \\ E_{Bdis\_\max} \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} \infty \\ . \\ \infty \end{bmatrix} \end{bmatrix}$

Version 4 Results

To be sure Version 4 is working as specified, two rate cases were tested. In the first, the purchasing price of energy is always lower than the selling price, but in the second, the selling price is higher than the purchasing price for three hours. The first case is to prove that by changing the objective function and constraints to include a dummy variable, other problems have not arisen, and this can be seen by comparing the dispatch in Figure 4.14 to the dispatch generated by Version 3.1 in Figure 4.12 previously. Both dispatches are identical, as they should be.

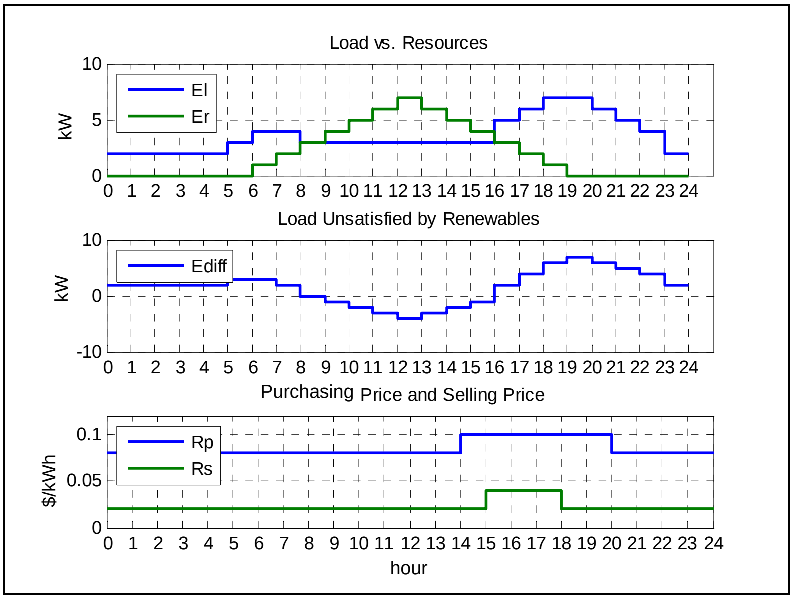

Figure 4.13: Load, Resources, and Rates; Version 4, Example 1

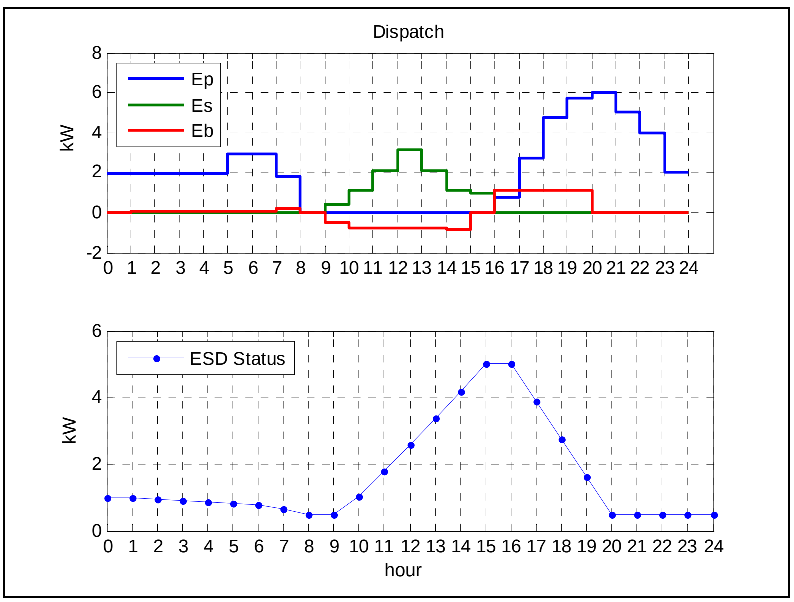

Figure 4.14: Dispatch Schedule; Version 4, Example 1

The second rate case, shown in Figure 4.15, includes a time period in which the selling price is higher than the purchasing price of energy. In all previous versions this would have led to an unbounded error and no feasible dispatch. However, Version 4 has handled this rate case and produced a feasible dispatch that satisfies all constraints.

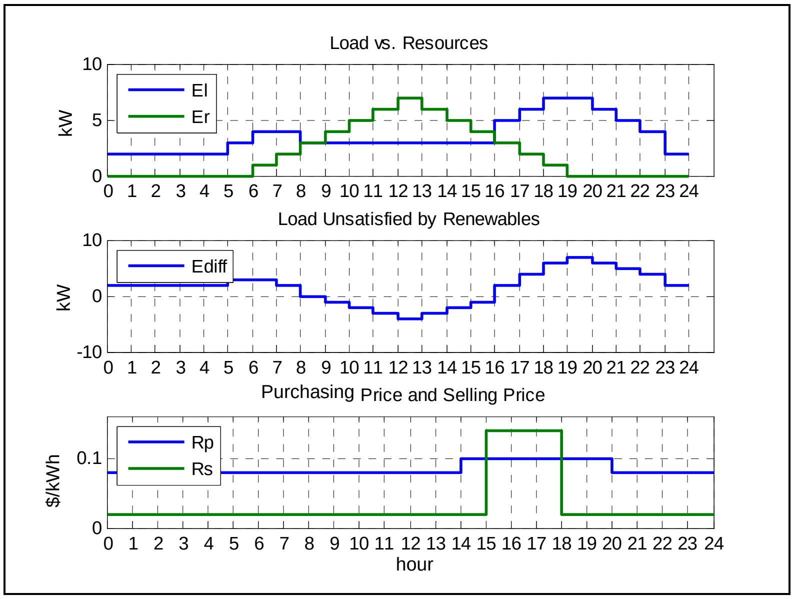

Figure 4.15: Load, Resources, and Rates; Version 4, Example 2

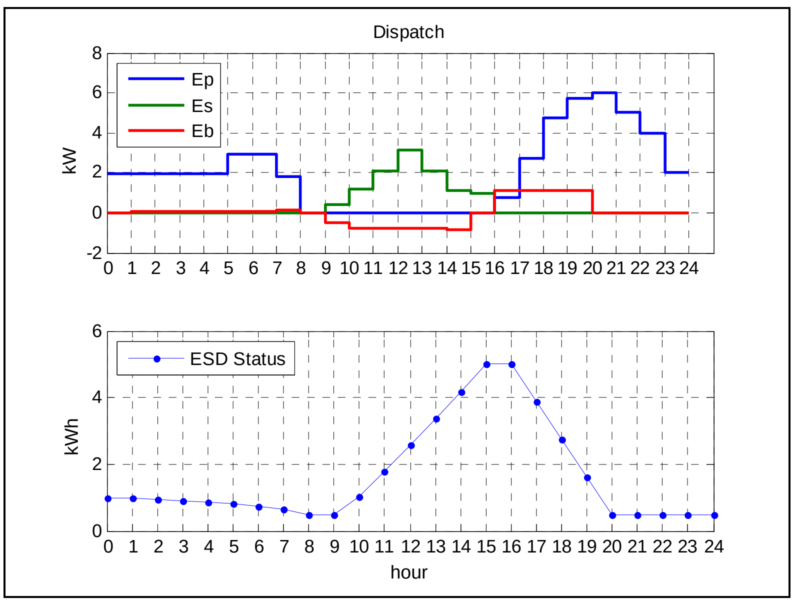

Figure 4.16: Dispatch Schedule; Version 4, Example 2

There is a problem with Version 4 though. Adding the dummy variable fixed the problem of buying and selling enormous amounts of energy in the same hour, but it created another problem in that the algorithm does not sell at times when it clearly should because the dummy variable limits the amount of energy that can be sold in hours when the selling rate is higher than the buying rate. So while Version 4 is producing a feasible result, it is still not the best solution available.

Take for example Figures 4.17 and 4.18. From the 12th to the 20th hour the selling price is much higher than the buying price. The solution created by Version 4 does sell some energy back during those hours, but actually sells more back to the grid in the hours leading up to that time span when the selling price is equal to the buying price. Without the restriction created by the dummy variable, the system would store more energy leading up to those hours to take advantage of the energy rates to make the most money.

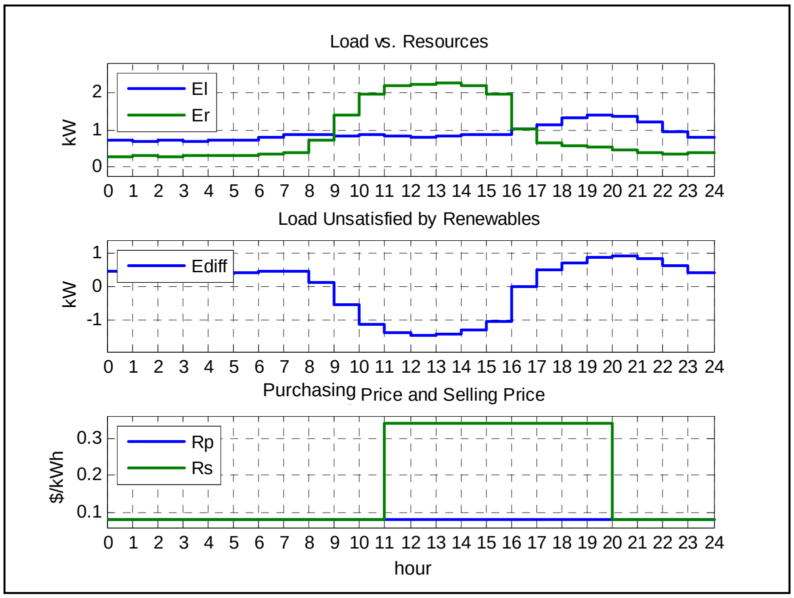

Figure 4.17: Load, Resources, and Rates; Version 4, Example 3

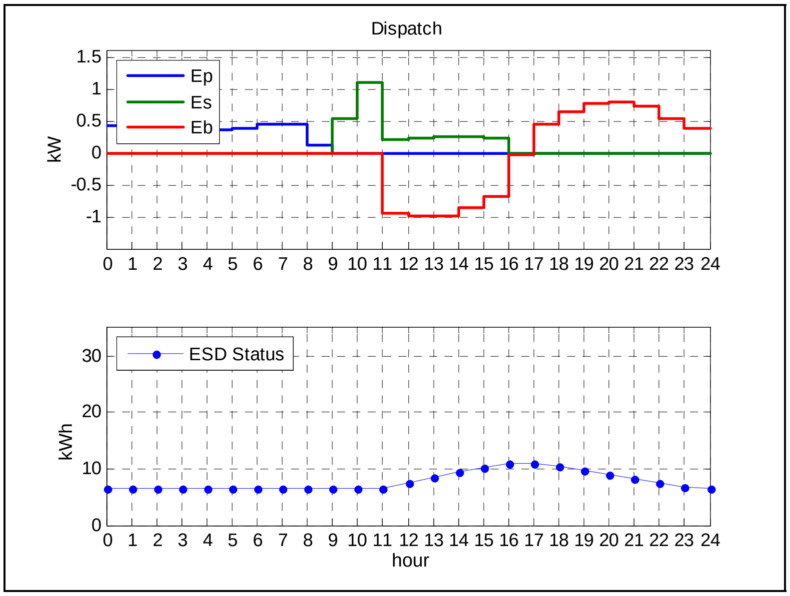

Figure 4.18: Dispatch Schedule; Version 4, Example 3

Version 5

Version 5 is a second attempt at solving the issue of buying and selling enormous amounts of energy in the same time period in which the selling price of energy is higher than the buying price. Rather than using a dummy variable as in Version 4, this version simply uses trial and error by setting either E_{Pi} or E_{Si} to zero in each time period when the selling price, R_S, is higher than the buying price, R_P. As mentioned previously in Version 4, either E_P or E_S should be zero in all time periods, and a feasible solution should show this[2]. It would be possible to use trial and error in all time periods by testing all combinations with either E_{Pi} or E_{Si} set to zero; but this happens naturally when R_P is higher than R_S because cost increases when E_P and E_S grow. Additionally, in a 24 period dispatch, 2^{24} (equal to 16,777,216) combinations would have to be

---

[2] An attempt was made to forces these variables to zero using two dummy variables u and v such that:

$$u_i v_i = 0$$

$$u_i + v_i = 0$$

So that one variable is always equal to 1 and the other is always equal to 0. These variables could then be multiplied by the energy flow terms as follows:

$$u_i E_{si} + v_i E_{pi}$$

However, this is clearly not a constraint that could be implemented as an LP, but it is useful to note as this work may be used in re-implementing the algorithm as a quadratic program sometime in the future.

attempted which would obviously take far too long (at one solution every 0.3s, it would take about 59 days to find them all and select the best one). Fortunately, only the peak hours of each day, at the very most about 9 hours, would have a selling price higher than the buying price leaving only 2^9 (equal to 512) combinations which is quickly handled by a computer. Hours when the selling price and purchasing price are equal must also be handled. In cases of net metering though, this would be 24 hours out of the day. As has already been mentioned, 24 trial and error periods take far too long to find a solution. Therefore, when the selling and purchasing rates are the same, the selling rate is made slightly lower, i.e. 0.01% less than what it actually is, before the LP is used to get around the issue of the selling price being equal to or larger than the buying price.

This method of trial and error certainly creates both feasible and infeasible solutions. In each simulation, the cheapest feasible solution is kept as the working dispatch schedule.

Version 5 Linear Program

Decision Variables:

Decision Variables:	R_{pi}	=	*purchasing rate (cost) in period i*
	R_{si}	=	*selling rate (price) in period i*
	R_B	=	*cycling cost coefficient*
	E_{Li}	=	*electrical load in period i*
	E_{Ri}	=	*amount of energy that can be extracted from renewable resources in period i*
	E_{B0}	=	*initial battery charge*
	E_{BCmin}	=	*minimum battery capacity*
	E_{BCmax}	=	*maximum battery capacity*
	E_{Bdis_max}	=	*maximum hourly, or other period, discharge*
	E_{Bdis_min}	=	*maximum hourly, or other period, charge*
	e_{dis}	=	*ESD discharging efficiency*
	e_{char}	=	*ESD charging efficiency*

Parameters: E_{pi} = *amount of energy purchased in period i*

E_{si} = *amount of energy sold in period i*

E_{Bi+} = *amount of energy flowing from the battery in time period* = *i (discharging)*

E_{Bi-} = *amount of energy flowing to the battery in time period i (charging)*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i}$$

Subject To:

$$\left.\begin{aligned} &E_{Pi} = 0 \\ &E_{Si} = 0 \end{aligned}\right\} \textit{Dependent on guess and check iteration}$$

$$\left.\begin{aligned} &E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri} \\ &e_{dis} \times (-E_{B1-} - E_{B2-} - \ldots - E_{Bi-}) + \ldots \\ &\ldots + e_{char} \times (-E_{B1+} - E_{B2+} - \ldots - E_{Bi+}) \le E_{BC\max} - E_{B0} \\ &e_{dis} \times (E_{B1-} + E_{B2-} + \ldots + E_{Bi-}) + \ldots \\ &\ldots + e_{char} \times (+E_{B1+} + E_{B2+} + \ldots + E_{Bi+}) \le E_{B0} - E_{BC\min} \\ &0 \le E_{Bi+} \le E_{Bdis\_\max} \\ &E_{Bchar\_\max} \le E_{Bi-} \le 0 \end{aligned}\right\} \textit{for } i = 1 \textit{ to } n$$

Where: i = *the period (typically the hour of the day)*

n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Cost Function

The cost function no longer includes a dummy variable and is identical to that of Version 3.1.

Table 4.27: Cost Function, Version 5

Mathematical representation	$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i}$
Defined in MATLAB	$x = [E_P \quad E_S \quad E_{B+} \quad E_{B-}]$ $f = \left[R_{Pi} \quad -R_{Si} \quad R_B \quad -R_B\right]'$

Defining the Constraints

Like the cost function, all of the constraints differ from those of Version 4 since the dummy variable is no longer present, but with the exception for the equality constraint, all constraints in Version 5 are equal to those of Version 3.1.

Equality Constraints

The equality constraint changes in both content and size depending on which periods have a higher selling price than buying price. Take for example a case when the selling price of energy is higher than the buying price in the 1st, 2nd, and 4th hours of a 24 hour dispatch. Since there are three hours when $R_P > R_S$, there are be 2^3 (equal to 8) combinations that need to be attempted. Table 4.28 below shows what these combinations are. A zero in the table indicates that the element in question is forced to zero and a dash indicates that the element is undefined by the equality constraint.

Table 4.28: Guess and Check Combinations Example

Simulation	E_{P1}	E_{P2}	E_{P4}	E_{S1}	E_{S2}	E_{S4}
000	-	-	-	0	0	0
001	-	-	0	0	0	-
010	-	0	-	0	-	0
011	-	0	0	0	-	-
100	0	-	-	-	0	0
101	0	-	0	-	0	-
110	0	0	-	-	-	0
111	0	0	0	-	-	-

So for the fourth guess and check combination of this example, the equality constraints would be defined as follows.

Table 4.29: Equality Constraint Example, Version 5

Mathematical representation	$E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri}$, *for i = 1 to n* $E_{P2} = 0$, $E_{P4} = 0$, $E_{S1} = 0$
Defined in MATLAB	$Aeq = \begin{bmatrix} \begin{bmatrix} eye(n \times n) \end{bmatrix} & \begin{bmatrix} -eye(n \times n) \end{bmatrix} & \begin{bmatrix} eye(n \times n) \end{bmatrix} & \begin{bmatrix} eye(n \times n) \end{bmatrix} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & . & 0 \\ 0 & 1 & 0 & 0 & . & 0 \\ 0 & 0 & 0 & 1 & . & 0 \end{bmatrix} & \begin{bmatrix} 1 & 0 & . & 0 \\ 0 & 0 & . & 0 \\ 0 & 0 & . & 0 \end{bmatrix} & \begin{bmatrix} zeros(3 \times n) \end{bmatrix} & \begin{bmatrix} zeros(3 \times n) \end{bmatrix} \end{bmatrix}$ $beq = \begin{bmatrix} \begin{bmatrix} E_{L1} - E_{R1} \\ E_{L2} - E_{R2} \\ . \\ . \\ E_{Ln} - E_{Rn} \end{bmatrix} \\ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \end{bmatrix}$

Inequality Constraints

The inequality constraints are equal to those in Version 3.1 and are shown again in Table 4.29.

Table 4.30: Inequality Constraints, Version 5

Mathematical representation	$e_{dis} \times (-E_{B1-} - E_{B2-} - ... - E_{Bi-}) + e_{char} \times (-E_{B1+} - E_{B2+} - ... - E_{Bi+}) \le E_{BC\max} - E_{B0}$, *for i = 1 to n* $e_{dis} \times (E_{B1-} + E_{B2-} + ... + E_{Bi-}) + e_{char} \times (+E_{B1+} + E_{B2+} + ... + E_{Bi+}) \le E_{B0} - E_{BC\min}$, *for i = 1 to n*
Defined in MATLAB	$A = \begin{bmatrix} [\, zeros(n \times 2n) \,] & [\, -e_{dis} \times tril(ones(n \times n)) \,] & [\, -e_{char} \times tril(ones(n \times n)) \,] \\ [\, zeros(n \times 2n) \,] & [\, e_{dis} \times tril(ones(n \times n)) \,] & [\, e_{char} \times tril(ones(n \times n)) \,] \end{bmatrix}$ $b = \begin{bmatrix} \begin{bmatrix} E_{BC\max} - E_{B0} \\ E_{BC\max} - E_{B0} \\ . \\ . \\ E_{BC\max} - E_{B0} \end{bmatrix} \\ \begin{bmatrix} E_{B0} - E_{BC\min} \\ E_{B0} - E_{BC\min} \\ . \\ . \\ E_{B0} - E_{BC\min} \end{bmatrix} \end{bmatrix}$

Upper and Lower Bounds

The upper and lower bounds are also equal to those in Version 3.1 and are shown again in Table 4.31.

Table 4.31: Upper and Lower Bounds

Mathematical representation	$0 \le E_{Bi+} \le E_{Bdis\_\max}$, *for i = 1 to n* $E_{Bchar\_\max} \le E_{Bi-} \le 0$, *for i = 1 to n*
Defined in MATLAB	$lb = \begin{bmatrix} \begin{bmatrix} 0 \\ . \\ . \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} -E_{Bchar\_\max} \\ . \\ -E_{Bchar\_\max} \end{bmatrix} \end{bmatrix}$ $ub = \begin{bmatrix} \begin{bmatrix} \infty \\ . \\ . \\ . \\ \infty \end{bmatrix} \\ \begin{bmatrix} E_{Bdis\_\max} \\ . \\ E_{Bdis\_\max} \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \end{bmatrix}$

Version 5 Results

To show that Version 5 can handle both situations where the purchasing price is always higher than the selling price and situations where the selling price is higher in some hours Figures 4.19 through 4.22 are given. It can be seen in Figure 4.19 that the same inputs were used as in testing of Version 3.1 and Version 4 when $R_P > R_S$ in all hours of the day. It can further be seen by comparing Figure 4.20 to Figures 4.12 and 4.14 that Version 5 produces the same dispatch as Versions 3.1 and 4 under those conditions. This means that Version 5 is working properly for rate cases when the selling price is always lower then the purchasing price.

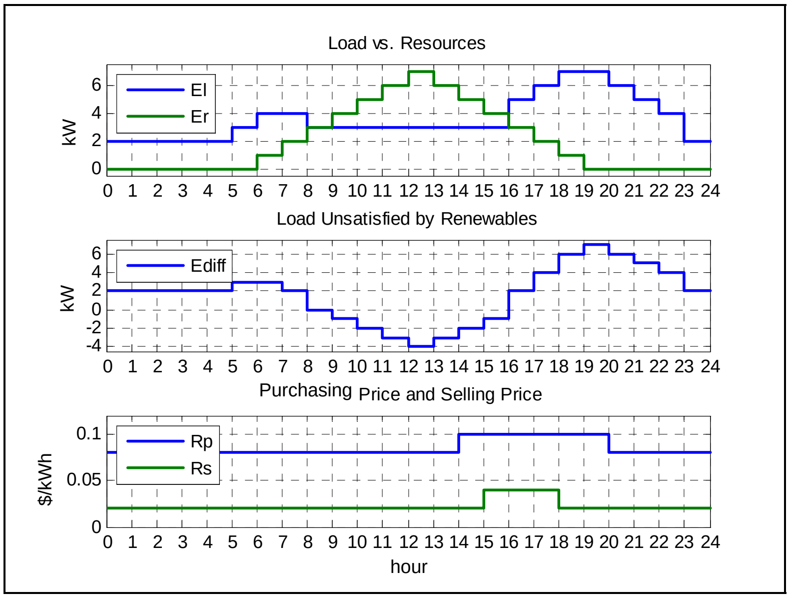

Figure 4.19: Load, Resources, and Rates; Version 5, Example 1

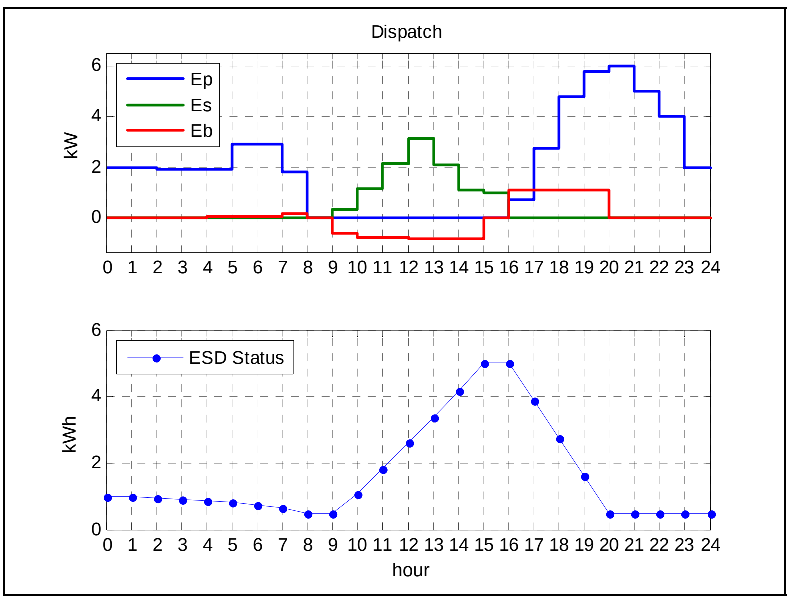

Figure 4.20: Load, Resources and Rates; Version 5, Example 1

Figure 4.21 shows an example of when some hours have a higher selling rate than purchasing rate and Figure 4.22 is the resulting dispatch generated by Version 5. These are the same load, resource, and rate profiles that were tested on Version 4, the results of which may be viewed in Figures 4.15 and 4.16. The dispatch generated by Version 5 is slightly different from the one generated by Version 4, as it sells slightly more energy in the time when the selling rate is higher than the buying rate. This is what should be expected though as the system is no longer limited in these situations. The system is now making better use of the increased selling rate.

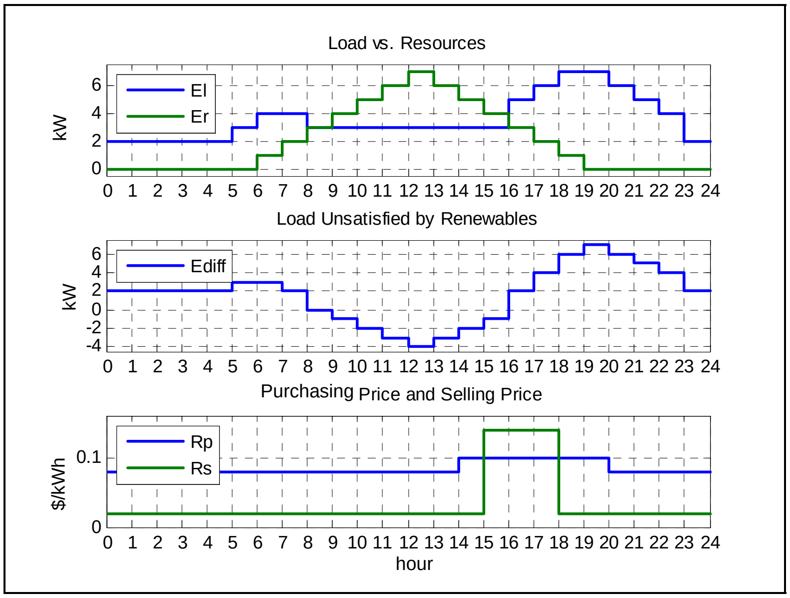

Figure 4.21: Load, Resources, Rates; Version 5, Example 2

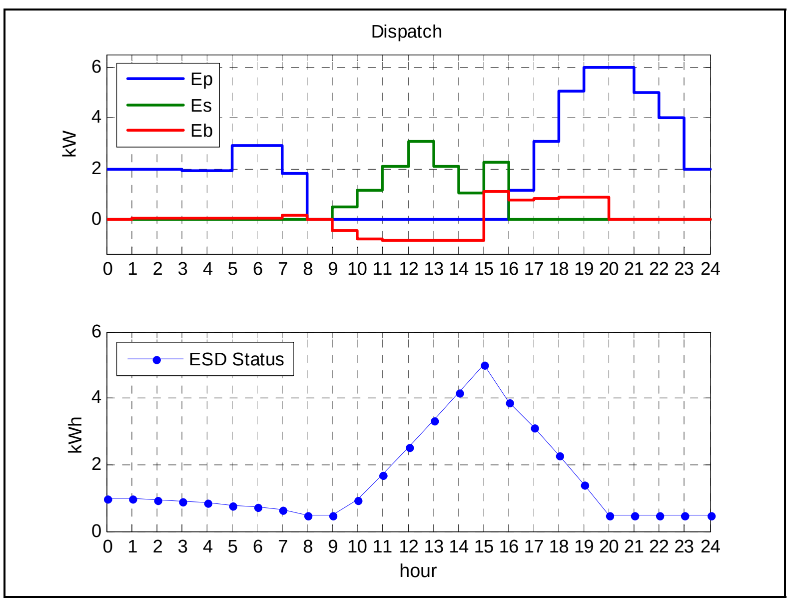

Figure 4.22: Dispatch Schedule; Version 5, Example 2

The real difference between Version 4 and 5 can be seen when the selling price becomes much higher than the purchasing price for several hours of the day. Figure 4.23 shows the inputs that were used to test this scenario. These are the same inputs that were given to Version 4 to show that cheaper dispatches could be created than what Version 4 was finding (see Figure 4.17 and 4.18). The total cost of the dispatch created by Version 4 when using these inputs is -$0.28. When using Version 5 the cost is reduced much further to -$10.53.

In this case the system is not only optimizing the dispatch of the renewable energy, but also purchasing a large amount of excess from the grid in the morning hours to get the most benefit out of the increased selling rate. By doing so, the system is shifting a great deal of load for the utility to the morning hours when the utility can easily meet demand, as indicated by these extravagant electric rates.

It can also be seen that towards the end of the time period when the selling rate is higher than the buying rate, the battery is charged and discharged as much as possible to make the most use of the energy prices. In a real situation, the utility would most likely want to avoid the system purchasing energy every other hour during peak demand time just to sell it right back, since that would be detrimental to load leveling. Therefore, the algorithm should be amended to prevent this from happening.

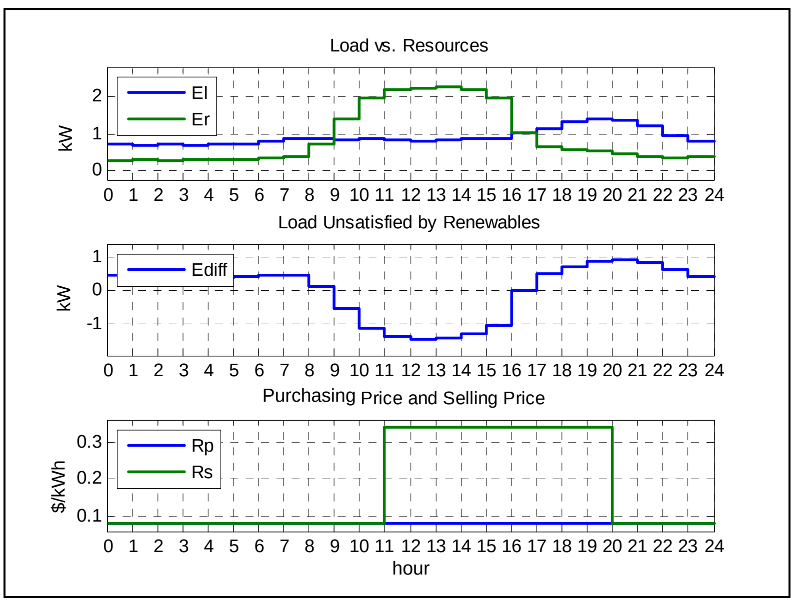

Figure 4.23: Load, Resources, and Rates; Version 5, Example 3

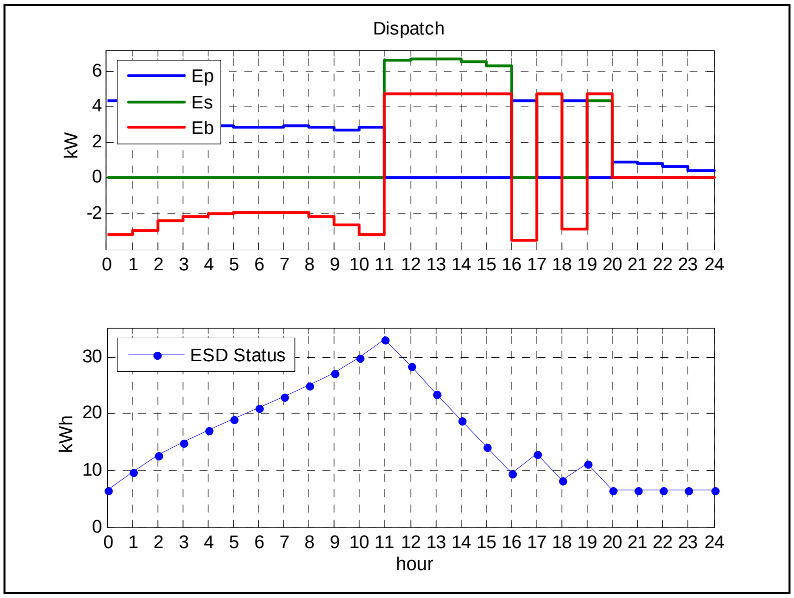

Figure 4.24: Dispatch Schedule; Version 5, Example 3

Version 5.1

While Version 5 was able to solve the problem of the algorithm creating a dispatch in which enormous amounts of energy are purchased and sold in the same hour during times when the purchasing price is lower the selling price, it still had one detrimental issue associated with it. The battery would discharge as quickly as possible during that rate time in order to recharge and discharge again in the following hours. While this makes the most sense economically for the customer, it would be detrimental to load leveling and the utility will undoubtedly not allow it. Therefore the constraints must be modified to prevent this from happening; and the best way to do this is to not allow battery charging if the selling rate is higher than the purchasing rate. This can easily be done by modifying the bounds set on the battery. While the other constraints do not need to be changed from the previous version, they are shown again for completeness, as this is the final and working version.

Version 5.1 Linear Program

Decision Variables:

R_{pi} = *purchasing rate (cost) in period i*

R_{si} = *selling rate (price) in period i*

R_B = *cycling cost coefficient*

E_{Li} = *electrical load in period i*

E_{Ri} = *amount of energy that can be extracted from renewable resources in period i*

E_{B0} = *initial battery charge*

E_{BCmin} = *minimum battery capacity*

E_{BCmax} = *maximum battery capacity*

E_{Bdis_max} = *maximum hourly, or other period, discharge*

E_{Bdis_min} = *maximum hourly, or other period, charge*

e_{dis} = *ESD discharging efficiency*

e_{char} = *ESD charging efficiency*

Parameters: E_{pi} = *amount of energy purchased in period i*

E_{si} = *amount of energy sold in period i*

E_{Bi+} = *amount of energy flowing from the battery in time period* = *i (discharging)*

E_{Bi-} = *amount of energy flowing to the battery in time period i (charging)*

Minimize: $$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i}$$

Subject To:

$$\left.\begin{array}{l} E_{Pi} = 0 \\ E_{Si} = 0 \end{array}\right\} \textit{Dependent on guess and check iteration}$$

$$\left.\begin{array}{l} E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri} \\ \\ e_{dis} \times (-E_{B1-} - E_{B2-} - \ldots - E_{Bi-}) + \ldots \\ \ldots + e_{char} \times (-E_{B1+} - E_{B2+} - \ldots - E_{Bi+}) \le E_{BC\max} - E_{B0} \\ \\ e_{dis} \times (E_{B1-} + E_{B2-} + \ldots + E_{Bi-}) + \ldots \\ \ldots + e_{char} \times (+E_{B1+} + E_{B2+} + \ldots + E_{Bi+}) \le E_{B0} - E_{BC\min} \\ \\ 0 \le E_{Bi+} \le E_{Bdis\_\max} \end{array}\right\} \textit{for } i = 1 \textit{ to } n$$

$E_{Bchar\_\max} \le E_{Bi-} \le 0$, *when* $E_{Pi} \ge E_{Si}$ *when* $E_{Pi} \ge E_{Si}$

$0 \le E_{Bi-} \le 0$, *when* $E_{Pi} \le E_{Si}$ *when* $E_{Pi} \le E_{Si}$

Where: i = *the period (typically the hour of the day)*

n = *the total number of periods in the dispatch schedule (typically 24, for an entire day)*

Defining the Cost function

The cost function implemented in Version 5.1 is given in Table 4.32. This is the same cost function that is use in Version 5.

Table 4.32: Cost Function; Version 5.1

Mathematical representation	$Cost = \sum_{i=1}^{n} E_{pi} \times R_{pi} - \sum_{i=1}^{n} E_{si} \times R_{si} + \sum_{i=1}^{n} E_{(B+)i} \times R_{(B+)i} - \sum_{i=1}^{n} E_{(B-)i} \times R_{(B-)i}$
Defined in MATLAB	$x = [E_P \quad E_S \quad E_{B+} \quad E_{B-}]$ $f = \left[R_{Pi} \quad -R_{Si} \quad R_B \quad -R_B\right]'$

Defining the Constraints

Equality Constraints

The equality constraints for Version 5.1 are given in Table 4.33. They are also the same as the equality constraints used in Version 5. A more detailed description of the equality constraints are in the Version 5 discussion given previously.

Table 4.33: Equality Constraints Example; Version 5.1

Mathematical representation	$E_{Pi} - E_{Si} + E_{Bi+} + E_{Bi-} = E_{Li} - E_{Ri}, \quad \textit{for i = 1 to n}$ $E_{P2} = 0, \quad E_{P4} = 0, \quad E_{S1} = 0$
Defined in MATLAB	$Aeq = \begin{bmatrix} [\; eye(n \times n) \;] & [\; -eye(n \times n) \;] & [\; eye(n \times n) \;] & [\; eye(n \times n) \;] \\ \begin{bmatrix} 0 & 0 & 0 & 0 & . & 0 \\ 0 & 1 & 0 & 0 & . & 0 \\ 0 & 0 & 0 & 1 & . & 0 \end{bmatrix} & \begin{bmatrix} 1 & 0 & . & 0 \\ 0 & 0 & . & 0 \\ 0 & 0 & . & 0 \end{bmatrix} & [\; zeros(3 \times n) \;] & [\; zeros(3 \times n) \;] \end{bmatrix} \quad beq = \begin{bmatrix} \begin{bmatrix} E_{L1} - E_{R1} \\ E_{L2} - E_{R2} \\ . \\ . \\ E_{Ln} - E_{Rn} \end{bmatrix} \\ \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \end{bmatrix}$

Inequality Constraints

The inequality constraints are also the same as Version 5.1. They are shown in Table 4.34.

Table 4.34: Inequality Constraints Version 5.1

Mathematical representation	$e_{dis} \times (-E_{B1-} - E_{B2-} - ... - E_{Bi-}) + e_{char} \times (-E_{B1+} - E_{B2+} - ... - E_{Bi+}) \le E_{BC\max} - E_{B0}$, *for i = 1 to n* $e_{dis} \times (E_{B1-} + E_{B2-} + ... + E_{Bi-}) + e_{char} \times (+E_{B1+} + E_{B2+} + ... + E_{Bi+}) \le E_{B0} - E_{BC\min}$, *for i = 1 to n*
Defined in MATLAB	$A = \begin{bmatrix} [\; zeros(n \times 2n) \;] & [\; -e_{dis} \times tril(ones(n \times n)) \;] & [\; -e_{char} \times tril(ones(n \times n)) \;] \\ [\; zeros(n \times 2n) \;] & [\; e_{dis} \times tril(ones(n \times n)) \;] & [\; e_{char} \times tril(ones(n \times n)) \;] \end{bmatrix}$ $b = \begin{bmatrix} \begin{bmatrix} E_{BC\max} - E_{B0} \\ E_{BC\max} - E_{B0} \\ . \\ . \\ E_{BC\max} - E_{B0} \end{bmatrix} \\ \begin{bmatrix} E_{B0} - E_{BC\min} \\ E_{B0} - E_{BC\min} \\ . \\ . \\ E_{B0} - E_{BC\min} \end{bmatrix} \end{bmatrix}$

Upper and Lower Bounds

The lower bounds are the only aspect of the dispatch algorithm that changes from the previous version; however the upper bounds remain the same. In all previous versions, the lower bounds set on the battery are simply the maximum charging rate. Here the lower bounds on the battery are set to zero at any time the selling price is higher than the buying price. That prevents the battery system from cycling during times when the selling price is higher than the buying price.

For example, if the selling price is higher than the buying price in hours 1, 2, and 4, the lower bounds on the battery should be set to zero in those hours. The upper and lower bounds for this example are given in Table 4.35.

Table 4.35: Upper and Lower Bounds Example; Version 5.1

Mathematical representation	$0 \le E_{Bi+} \le E_{Bdis\_\max}$, *for i = 1 to n* $E_{Bchar\_\max} \le E_{Bi-} \le 0$, $when\, E_{Pi} \ge E_{Si}$ $0 \le E_{Bi-} \le 0$, $when\, E_{Pi} \le E_{Si}$
Defined in MATLAB	$lb = \begin{bmatrix} \begin{bmatrix} 0 \\ . \\ . \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \\ \begin{bmatrix} 0 \\ 0 \\ -E_{Bchar\_\max} \\ 0 \\ -E_{Bchar\_\max} \\ . \\ -E_{Bchar\_\max} \end{bmatrix} \end{bmatrix}$ $ub = \begin{bmatrix} \begin{bmatrix} \infty \\ . \\ . \\ . \\ \infty \end{bmatrix} \\ \begin{bmatrix} E_{Bdis\_\max} \\ . \\ E_{Bdis\_\max} \end{bmatrix} \\ \begin{bmatrix} 0 \\ . \\ 0 \end{bmatrix} \end{bmatrix}$

Version 5.1 Results

Version 5.1 has been created to improve on Version 5 so that the battery does not cycle during times with the selling price is higher than the buying price. Under normal circumstances, when the selling price is not higher than the purchasing price, Version 5.1 produces dispatch schedules identical to Version 5. This can be seen by examining Figures 4.25 and 4.26 and comparing them to Figures 4.19 and 4.20, shown in the Version 5 results, which are already known to be accurate. The dispatch schedules generated by these two different LPs are identical.

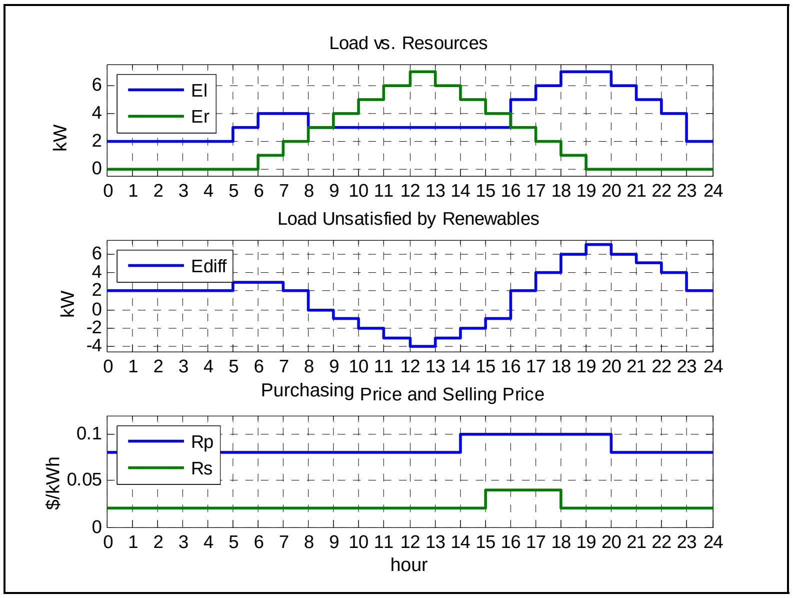

Figure 4.25: Loads, Resources, and Rates; Version 5.1, Example 1

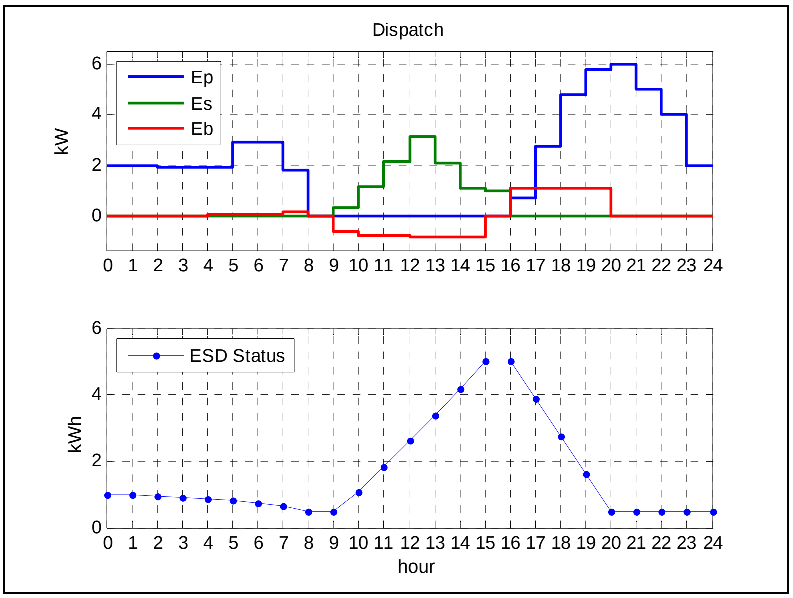

Figure 4.26: Dispatch Schedule; Version 5.1, Example 1

When the selling price is increased to a level higher than the purchasing price, the system still works to cut the peak load, see Figures 4.27 and 4.28, but it no longer cycles between charging the battery and discharging the battery as it had done previously in Version 5, see Figures 4.23 and 4.24. This is because the battery is now restricted from charging in times when the selling price is higher then the buying price.

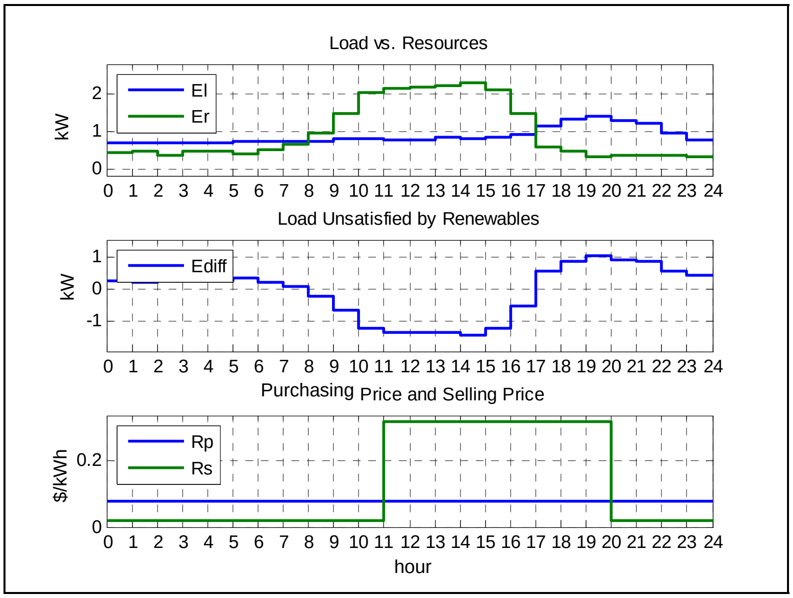

Figure 4.27: Load, Resources, and Rates; Version 5.1 Example 2

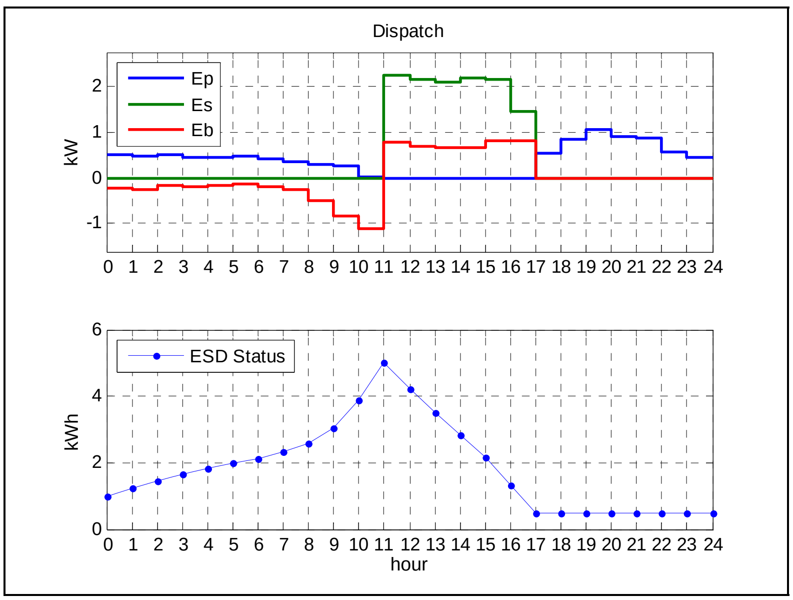

Figure 4.28: Dispatch Schedule; Version 5.1, Example 2

Version 5.1 is the final and working LP that is used for the IDDRR algorithm on which realistic simulations are run in the next chapter. This version takes into account all of the major non-idealities of a realistic system, and it is capable of handling any type of varying rate case possible.

CHAPTER 5 - Simulations and Results

Up to this point, all dispatches shown have been created for hypothetical systems with completely fabricated input data. For the sake of determining how effective the dispatching algorithm is, it should be implemented on realistic systems with real data for load and renewable resources and with real constraints. With the number of inputs to the system and the number of options available for each input, an unlimited number of simulations could be created. Several are shown here using the two different types of wind generators and the solar system already mentioned in Chapter 2. Five different rate cases are implemented on each system as well. For economic evaluation, the cost of energy when using the dispatching algorithm is compared to the cost of satisfying the load under the same rate case without the assistance of a renewable generator or ESD system.

Simulation Inputs

Several aspects of the simulation inputs are common to many of the case studies and are presented here individually.

Wind Data

Wind data was acquired for two locations though University of Utah's online database available at www.met.utah.edu/. The raw data was then processed to formulate data that would be a good representation of the surrounding area of each location.

Manhattan, KS Wind Data

The first set of hourly wind data for these simulations was taken at the Manhattan, KS airport (KMHK). The anemometer at the airport sits atop at tower that is approximately 30 feet tall. Hourly averages for this data set, prior to any adjustments, are shown in Figure 5.1 below. Just less than 5 years, 71 months to be exact, of hourly data was taken to formulate these averages. The data set is continuous from the beginning of 2003 to the end of November 2008. It can be seen that in all months, the wind is highest between the hours of 11:00 a.m. and 6 p.m., which should cover the beginning of the peak load hours. Unfortunately though, the peak wind months are March, April, and May while the peak load months in the area are June, July and August. The average for this data is 3.316m/s (7.419 mph).

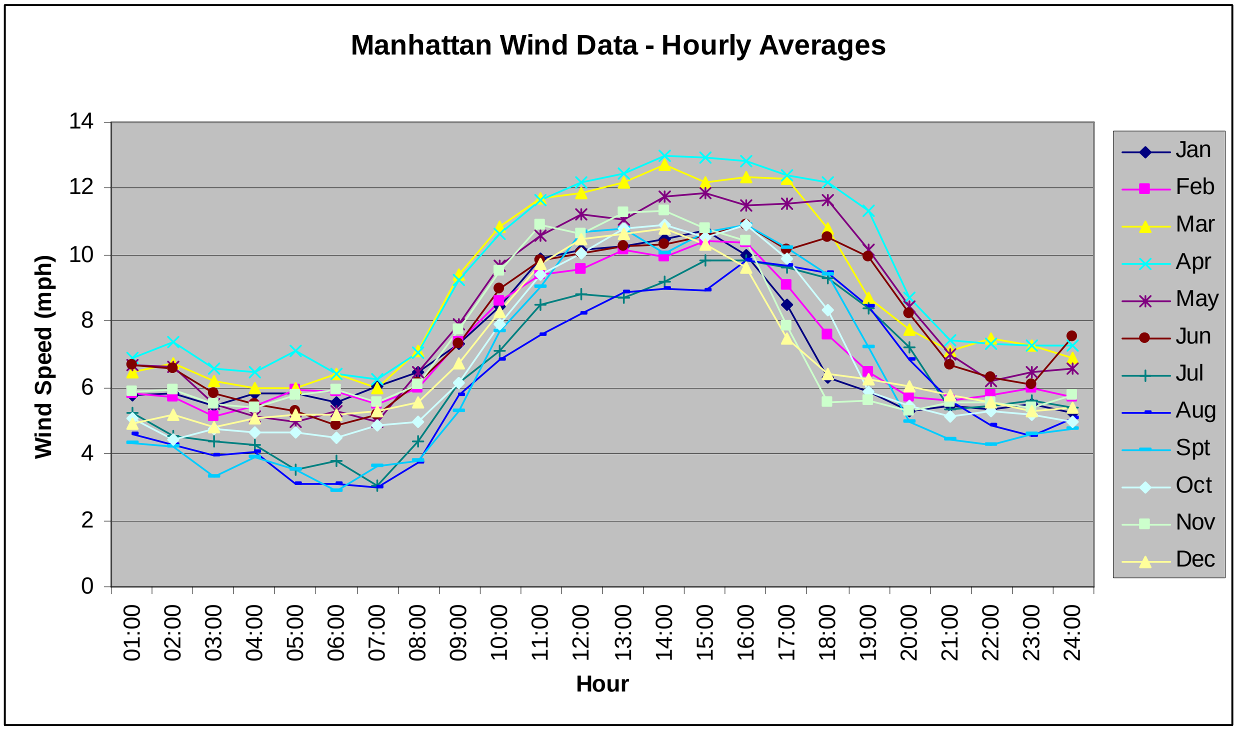

Figure 5.1: Manhattan Average Hourly Wind

However, the performance of wind turbines depends very heavily on how well they are sited, and it must be insured that this data set is a good representation of wind speeds in the area of Manhattan. First, the data must be extrapolated to a height of 50m, the height at which the Kansas Corporation Commission Wind Map specifies various wind classes. The data can be extrapolated using the equation below.

$$U(z)/U(z_r) = \ln\left(\frac{z}{z_0}\right) \Big/ \ln\left(\frac{z_r}{z_0}\right) \qquad [43]$$

where, *U(z) is the wind speed at height z*

$U(z_r)$ is the known wind speed at reference height z_r

Z_0 is the surface roughness factor

Z_0 values for various surfaces are given in Table 5.1. Given the terrain of KMHK, a surface roughness factor of 9mm should be appropriate.

Table 5.1: Surface Roughness Values [43]

Terrain Description	**Z_0 (mm)**
Very smooth, ice or mud	0.01
Calm open sea	0.20
Blown sea	0.50
Snow surface	3.00
Lawn Grass	8.00
Rough Pasture	10.00
Fallow Field	30.00
Crops	50.00
Few trees	100.00
Many trees, hedges, few buildings	250.00
Forest and woodlands	500.00
Suburbs	1500.00
Centers of cities with tall buildings	3000.00

Extrapolating the KMHK data to a height of 50m gives an average wind speed of 4.13 m/s. By looking at Table 5.2, one can see that this is only Class 1 wind, which is not a good representation of wind in the state of Kansas.

Table 5.2: Wind Classes [44]

Wind Class	50 Meter wind speed average	
	(m/s)	**(mph)**
Class1	0.0 – 5.6	0 – 12.5
Class 2	5.6 – 6.4	12.5 – 14.3
Class 3	6.4 – 7	14.3 – 15.7
Class 4	7 – 7.5	15.7 – 16.8
Class 5	7.5 – 8	16.8 – 17.9
Class 6	8 – 8.8	17.9 – 19.7
Class 7	>8.8	>19.7

Using AWS Truewind LLC's windNavigator application, available on the web at http://navigator.awstruewind.com/, the average wind speed in Manhattan proper is found to be 6.14 m/s, however this is at 60m. Extrapolated down to 50m, using the equations outlined previously, the average becomes 6.01m/s, which is still only class two wind. However, Manhattan proper lies somewhat in a valley. Approximately 5 miles outside the city of Manhattan in a more rural area, where residential wind turbines are more likely to be located anyways, is a much better wind location. This location is shown on the map generated by the windNavigator application in Figure 5.2.

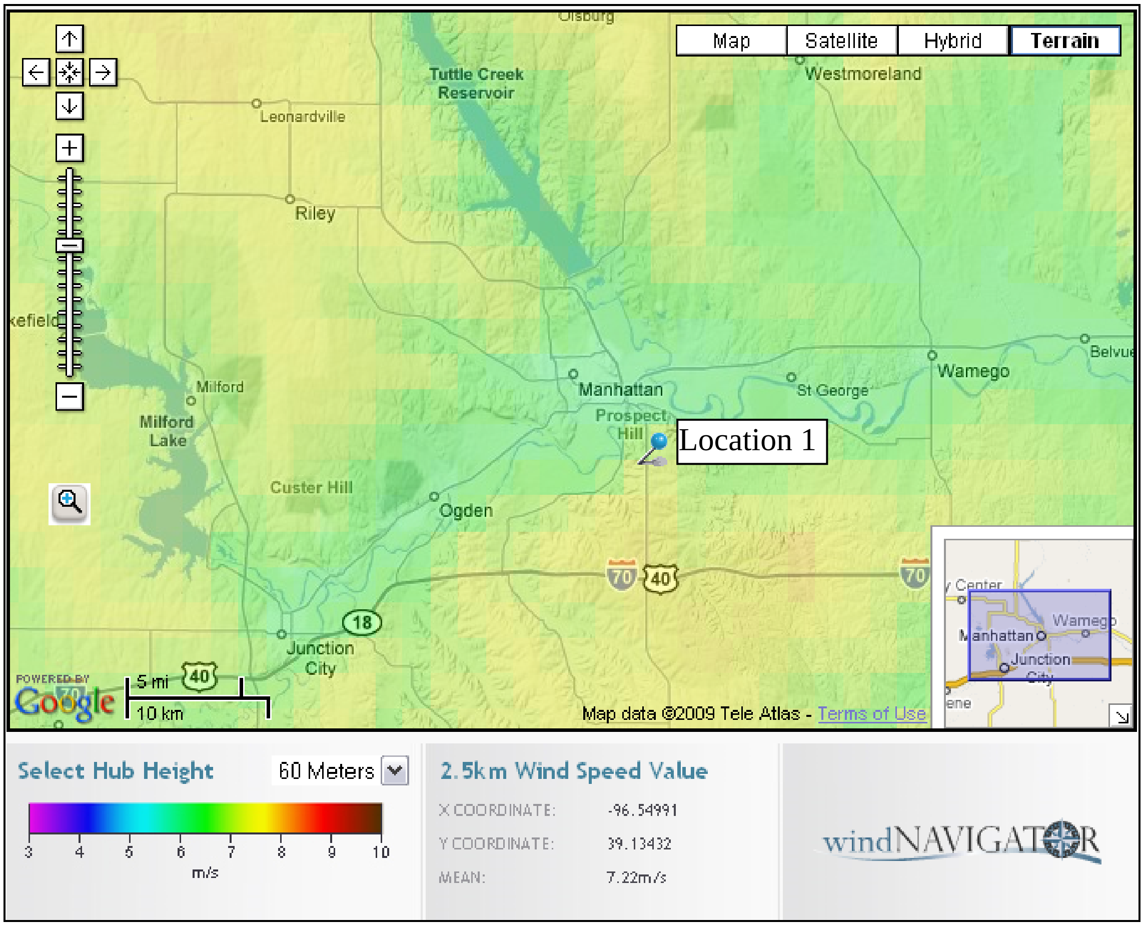

Figure 5.2: Manhattan, KS Wind Speed Map

At the spot marked “Location 1” by the pin in the map, the average wind speed is 7.22 m/s. However, this is at 60m. Extrapolated down to 50m, the average becomes 7.07 m/s, which is low class 4 wind. Using the Location 1 average along with the KMHK wind profile, a data set can be created that best represents hourly wind speeds for Location 1.

The average wind speed for Location 1, found with the windNavigator application, becomes 5.68m/s when extrapolated down to 30 feet, the point at which the KMHK data was taken. Since this is 1.71 times the average for the KMHK data, a multiplier of 1.71 should be used on the KMHK data. The data still retains its curve, but it is now a better representation of the more favorable wind speeds found around the city of Manhattan, KS. A summary of the wind speed data analysis and manipulation is shown in Tables 5.3, 5.4, and 5.5.

Table 5.3: KMHK Data Analysis and Classification

KMHK Wind speeds – Data Downloaded from MESO West	
Height	Average Wind Speed
30 feet (9.144 m) – original data taken at this height	3.316 m/s
50 m – height at which KCC wind class are defined	4.13 m/s – class 1
Class 1 wind is not a good representation of Kansas; a multiplier should be found for this data.	

Table 5.4: Manhattan Proper Data Analysis and Classification

Manhattan Proper Data – Average Wind Speed Found Using windNavigator	
Height	Average Wind Speed
60m – average wind speed listed at this height	6.14 m/s
50 m – height at which KCC wind class are defined	6.01 m/s – class 2

Table 5.5: Location 1 Data Analysis and Classification

Location 1 (Approximately 5 miles SE of Manhattan) Data – Average Wind Speed Found Using windNavigator	
Height	Average Wind Speed
60m –average listed at this height	7.22 m/s
50 m – height at which KCC wind class are defined	7.07 m/s – class 4
30 feet (9.144 m) – original data taken at this height	5.68 m/s – 1.71 times higher than KMHK average

Dodge City Wind Data

The second set of data was taken for Dodge City, KS, also though the University of Utah website (www.met.utah.edu/mesowest). Figure 5.3 shows the average hourly wind speeds for Dodge City prior to any adjustments. This data was formulated from 5 years of hourly wind speed data ending at the start of 2009.

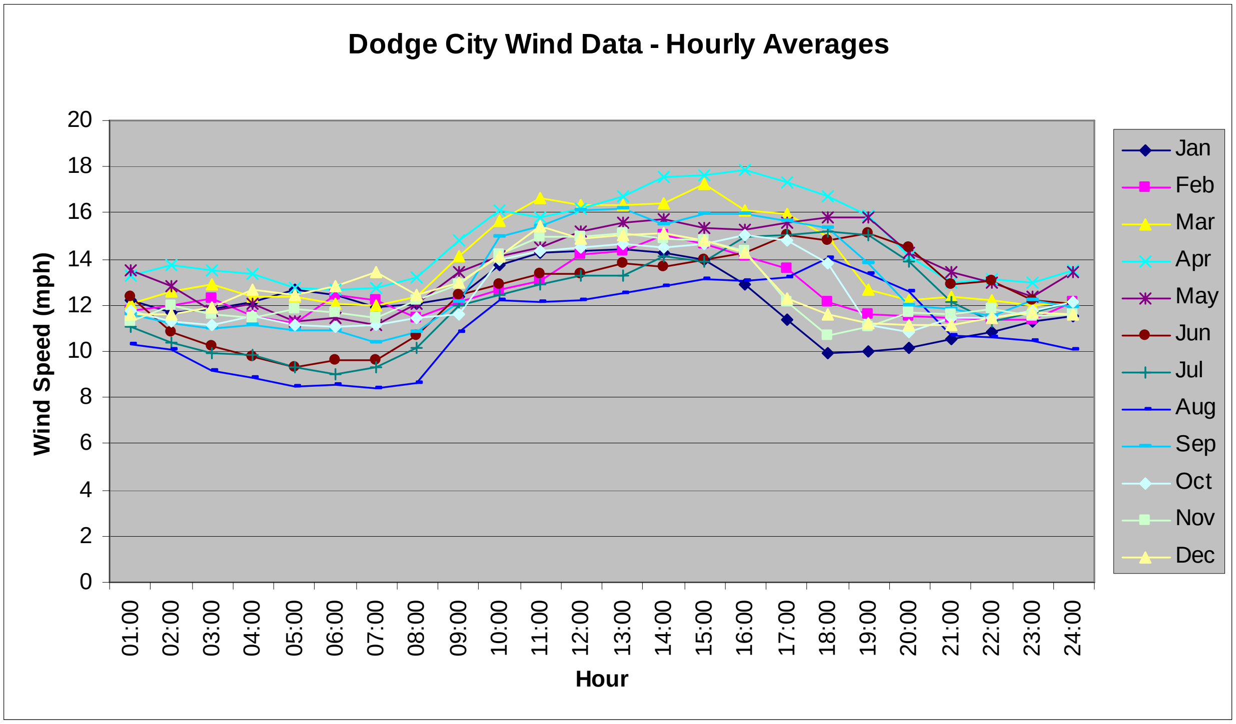

Figure 5.3: Dodge City Average Hourly Wind

Once again, it should be ensured that this data is a good representation of wind speeds around Dodge City area. The average for the data set is 12.82 mph (5.73 m/s), but the height at which the anemometer took this data is unknown. The 60m average found at a location roughly 5 miles outside of Dodge City is 8.1 m/s. The exact location is shown on Figure 5.4. Extrapolating the average down to 50m, assuming the same surface roughness as at KMHK, the average is 7.9 m/s, which is the high end of class 5 wind; and extrapolating down to 30 feet, since the MATLAB program is setup to work off a reference of 30 feet, the average is 6.4 m/s. Because the height that the original data was taken at is not known, an exact comparison cannot be made to the AWS average, but the data can still be adjusted by a multiplier of (6.4 m/s) / (5.73 m/s) = 1.12 for a good estimate of 30' wind speeds at Location 2.

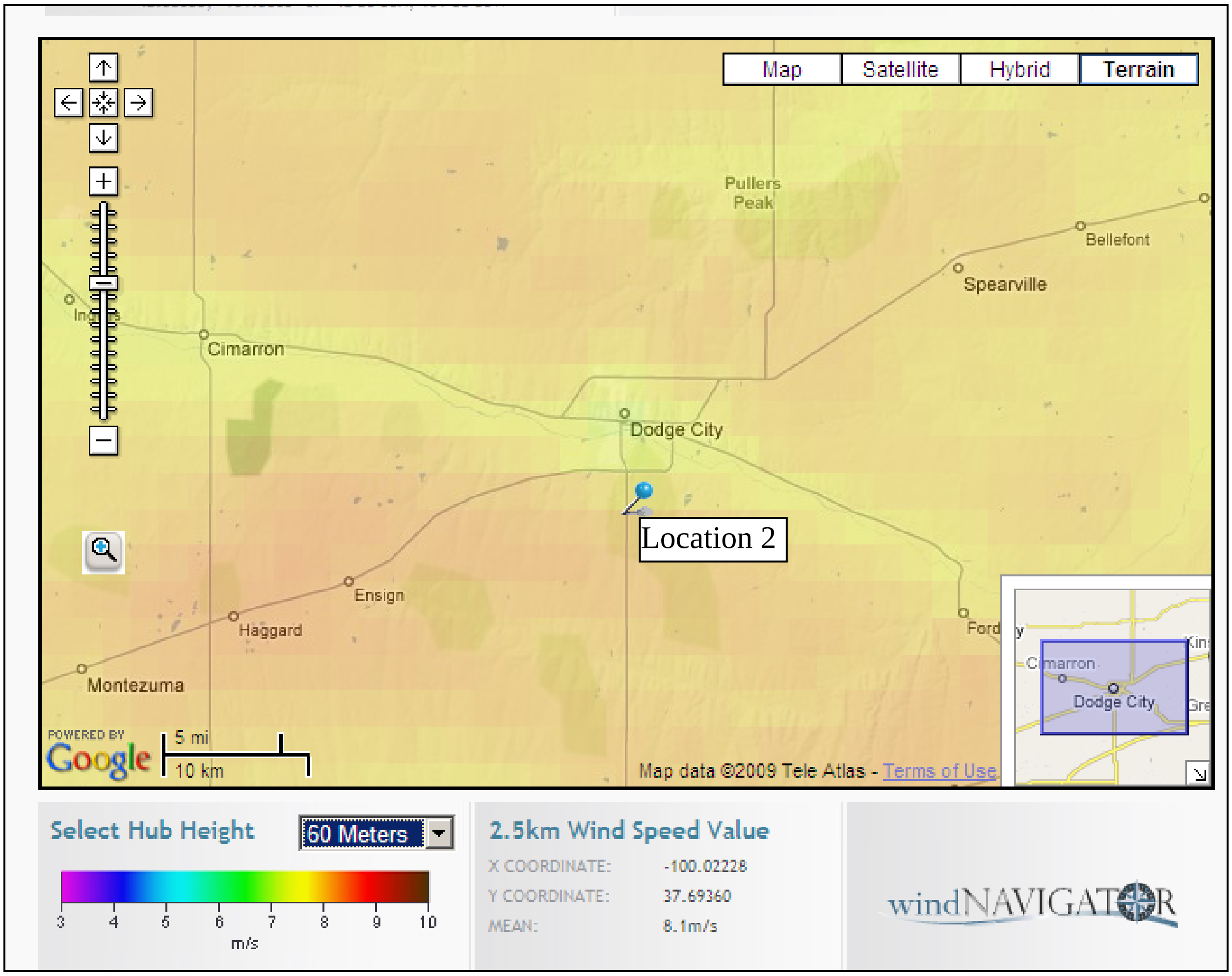

Figure 5.4: Dodge City, KS Wind Speed Map

Solar Data

Solar data was acquired for Manhattan, KS through the Kansas State University Agronomy Department. This data was taken on a horizontal collector and the monthly hour-by-hour averages are shown in Figure 5.5. This data was taken over the course of 4 continuous years ending at the start of 2009.

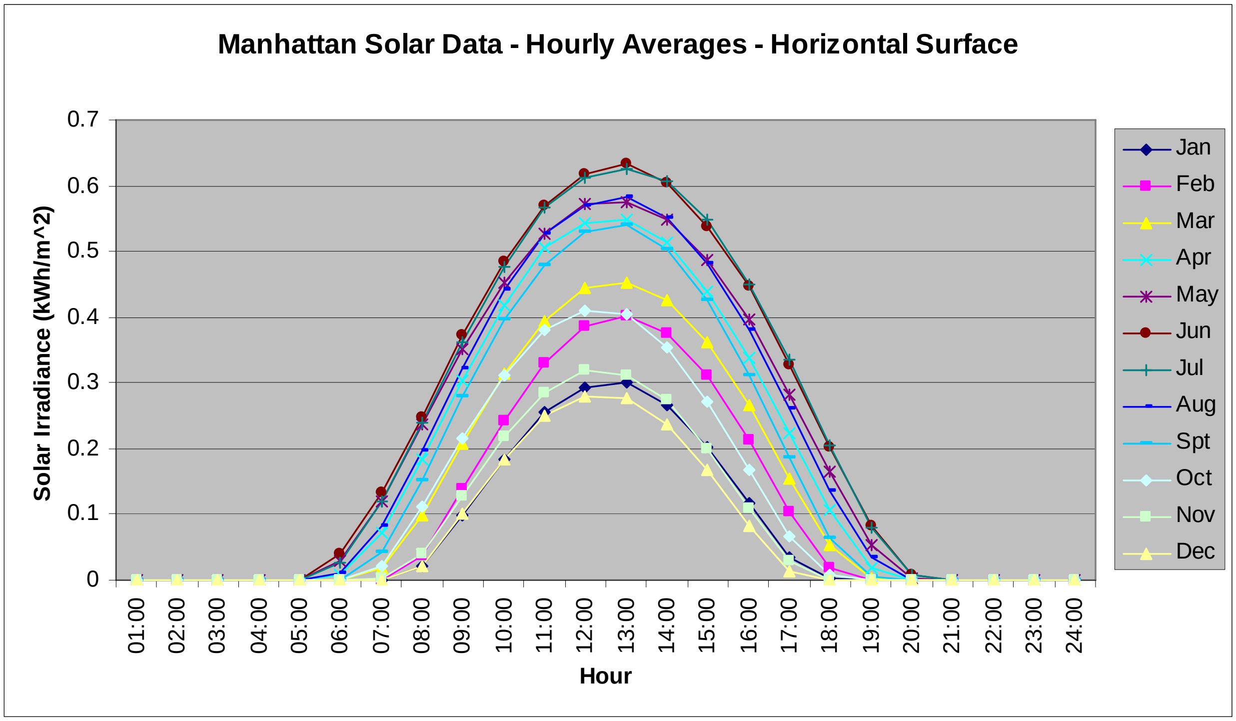

Figure 5.5: Manhattan Average Hourly Sunshine on a Flat Surface

Like the wind data, it should be verified that this data is an accurate representation of solar potential of the surrounding area since large buildings, trees, and even the landscape can have an impact on the amount of solar energy striking a surface. This solar data is verifiable by viewing the solar isonolation maps available online through the National Renewable Energy Laboratory (NREL) at http://rredc.nrel.gov/solar/old_data/nsrdb/redbook/atlas/ shown in Figure 5.6. The annual average number of peak sun days is in the 4 to 5 range. For the data set used to evaluate the performance of the solar system, the average annual number of peak sun days is 3.5, which is slightly lower than the NREL average but still sufficiently close. Therefore, this data is not be modified as the wind data has been.

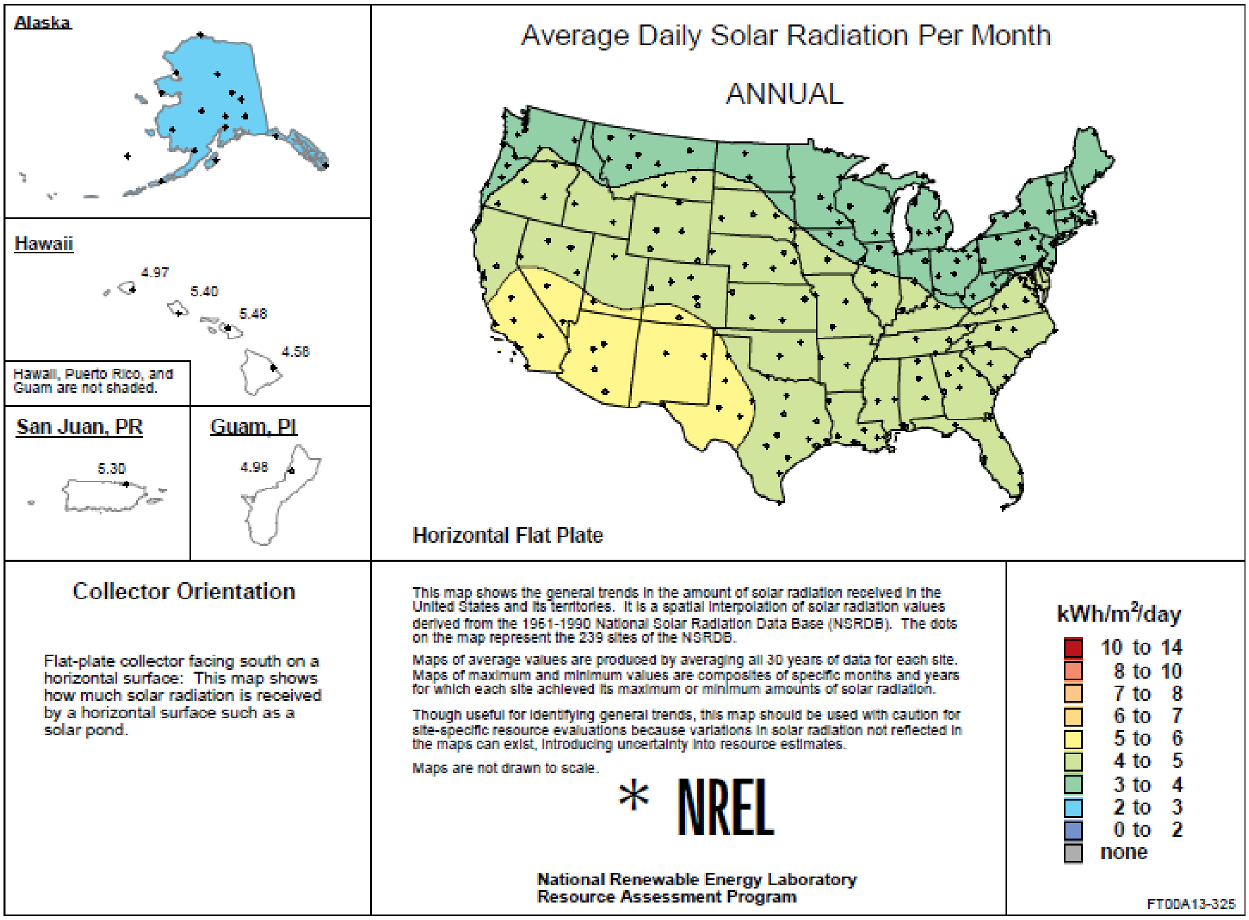

Figure 5.6: Average Annual Solar Irradiance

The data set presented in Figure 5.5 is for a flat plate collector. However, to optimize solar energy production, panels are usually tilted off horizontal as shown in Figure 5.7.

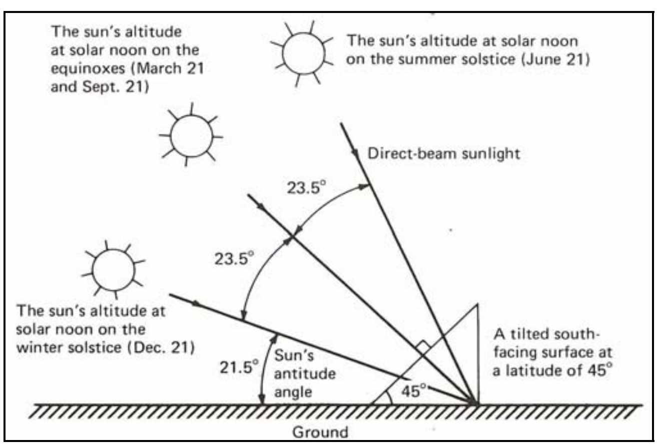

Figure 5.7: Optimum Solar Panel Tilt [32]

By setting the tilt at the same angle as the latitude and facing directly south, the most energy can be generated over the course of the year, as seen in Figure 5.8.

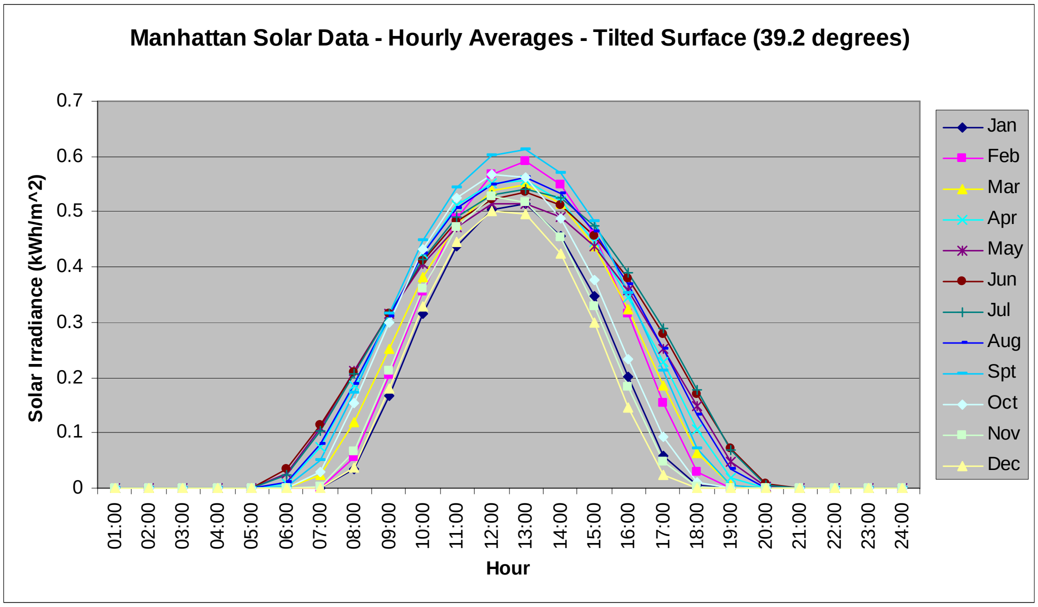

Figure 5.8: Manhattan Average Hourly Sunshine on a Surface Tilted at 39.2 degrees

On the other hand, to optimize solar performance during the summer months, the panel should be tilted at 15.7 degrees as shown in Figure 5.9.

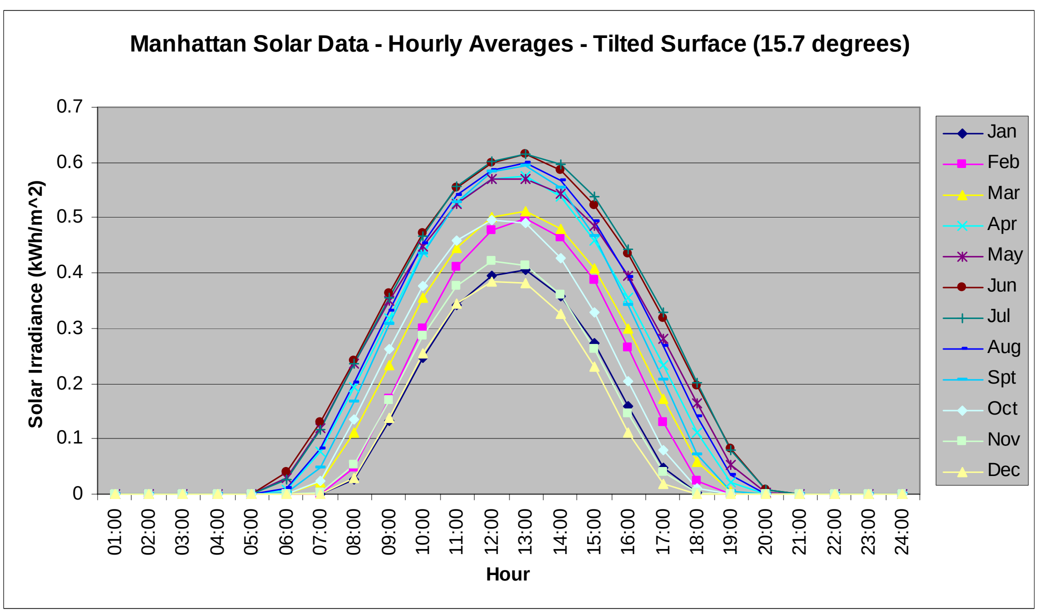

Figure 5.9: Manhattan Average Hourly Sunshine on a Surface Tilted at 15.7 degrees

The solar irradiance levels for angled surfaces relative to the horizontal surface data were computed using the set of equations described below in Figures 5.10 and 5.11.

$$\delta = 23.45 \sin\left(360\,\frac{284 + n}{365}\right) \qquad (3\text{-}3)$$

$$\omega_s = \cos^{-1}(-\tan\phi \tan\delta) \qquad (3\text{-}6)$$

$$\omega_s' = \min\begin{bmatrix}\cos^{-1}(-\tan\phi\tan\delta),\\ \cos^{-1}(-\tan(\phi-\beta)\tan\delta)\end{bmatrix} \qquad (3\text{-}7)$$

$$\overline{R}_b = \frac{\cos(\phi-\beta)\cos\delta\sin\omega_s' + (\pi/180)\omega'\sin(\phi-\beta)\sin\delta}{\cos\phi\cos\delta\sin\omega_s + (\pi/180)\omega_s\sin\phi\sin\delta} \qquad (3\text{-}8)$$

$$\frac{\overline{H}_D}{\overline{H}} = 1.390 - 4.027\overline{K}_T + 5.531\overline{K}_T^2 - 3.108\overline{K}_T^3 \qquad (3\text{-}9)$$

$$\overline{R} = \frac{\overline{H}_T}{\overline{H}} = \left(1 - \frac{\overline{H}_d}{\overline{H}}\right)\overline{R}_b + \frac{\overline{H}_d}{\overline{H}}\left(\frac{1+\cos\beta}{2}\right) + \rho\left(\frac{1-\cos\beta}{2}\right) \qquad (3\text{-}10)$$

Figure 5.10: Equations for Converting Solar Irradiance from a Horizontal Surface to a Tilted Surface [32]

where δ = the sun's declination angle ($-23.45°$ to $+23.45°$)
n = day of year (1 to 365)
ω_s = sunset hour angle on a horizontal surface
ω_s' = sunset hour angle on a tilted surface
ϕ = the site's latitude angle (0° to 90°) in the Northern Hemisphere
β = tilt or slope angle of a south-facing surface (0 to 180°; $\beta > 90$ means that the surface is facing downward)
$\overline{R}_b$ = ratio of monthly average daily direct-beam radiation on a tilted south-facing surface to that on a horizontal surface
$\overline{H}_d$ = monthly average daily diffuse radiation on a horizontal surface
$\overline{H}$ = monthly average daily total radiation on a horizontal surface
$\overline{K}_t$ = clarity coefficient: the ratio of insolation on the earth to insolation directly outside the earth's atmosphere
$\overline{R}$ = ratio of monthly average daily total radiation on a tilted south-facing surface to that on a horizontal surface
$\overline{H}_T$ = monthly average daily total radiation on a tilted south-facing surface
ρ = reflection coefficient: the fraction of light reflected by a surface (0 to 1)

Figure 5.11: Description of Variables [32]

Load Data

Actual load data was donated by a regional utility that serves both rural and metropolitan areas. The data set covered roughly four years of hourly load records for residential customers. However, the exact sizes and locations of the residences were not made available.

Residence 1

Residence 1, shown in Figure 5.12, is a summer-peaking load with an average peak demand of about 3.25 kWh from about 8 p.m. to 10 p.m. in July. The load in the non-summer months is much lower and does not vary throughout the day as much, although it still has a defined peak in the same hours as the summer months. The data used to find these averages was taken from 1/15/04 to 9/14/08.

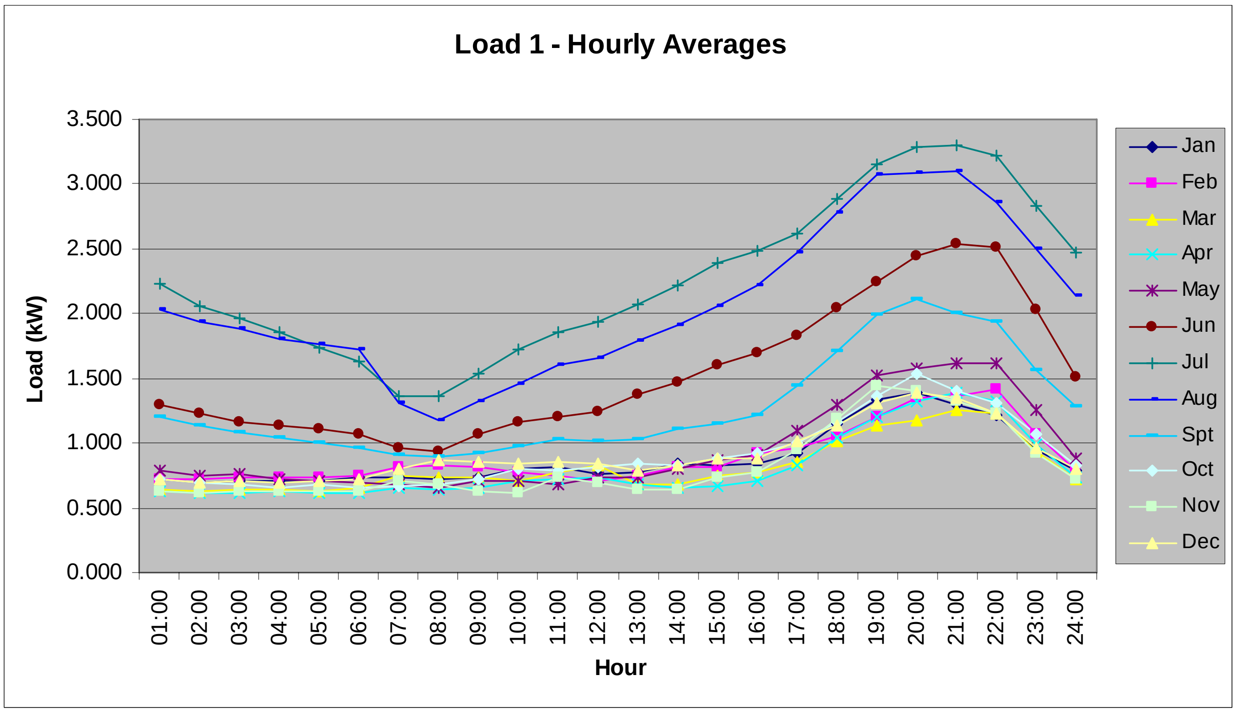

Figure 5.12: Daily Load Profile; Residence 1

Residence 2

The second residence, shown in Figure 5.13, has slightly less demand than the first, with about a 1 kWh difference in peak demand. The load in the two summer months of July and August is much higher than any of the other months with a well defined peak at about 7 p.m. The other months have a very flat profile and some even peak in the morning hours around 8 or 9 a.m. The load data for this residence was taken from 1/15/04 to 9/14/08.

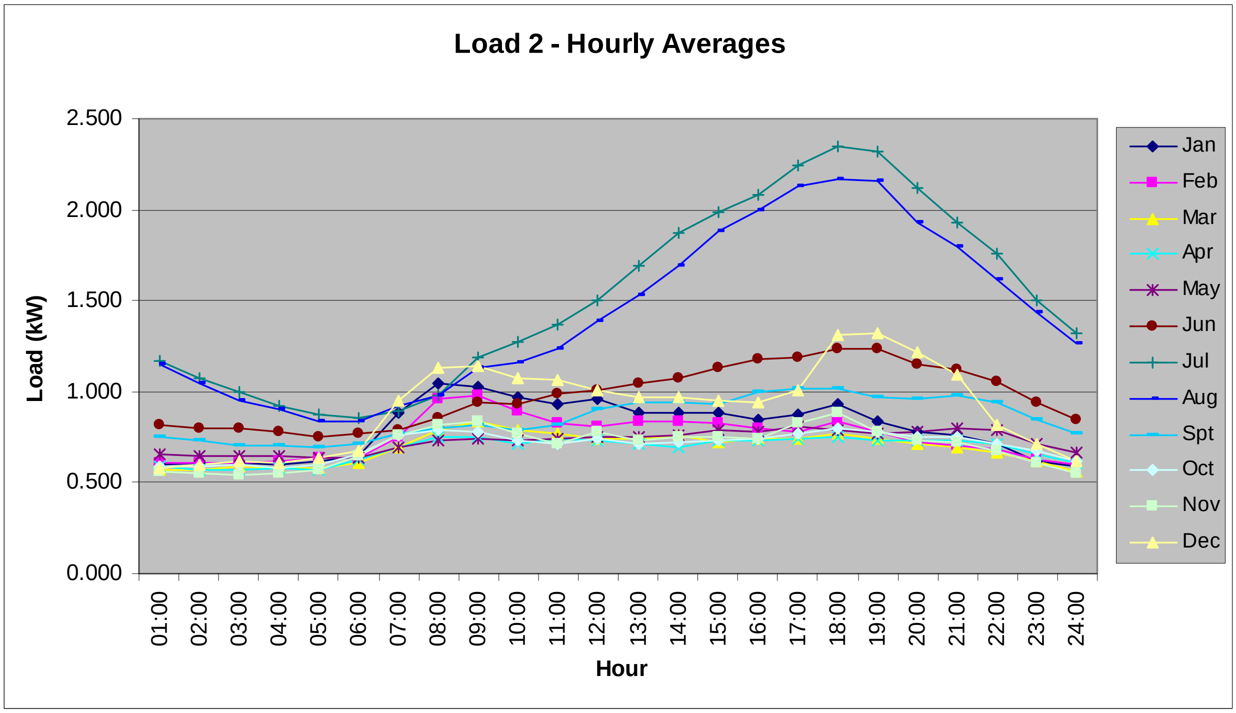

Figure 5.13: Daily Load Profile; Residence 2

Residence 3

The final residence, shown in Figure 5.14, has the largest overall demand and has the lowest variation of energy usage from month to month. In all months, the load increases steadily beginning at about 7 a.m. and peaks at about 10 p.m. In the early afternoon, from about noon to 4 p.m., the summer months had higher demand, but the overall average peak occurs in February. The data for this residence was taken from 5/26/04 to 8/28/08.

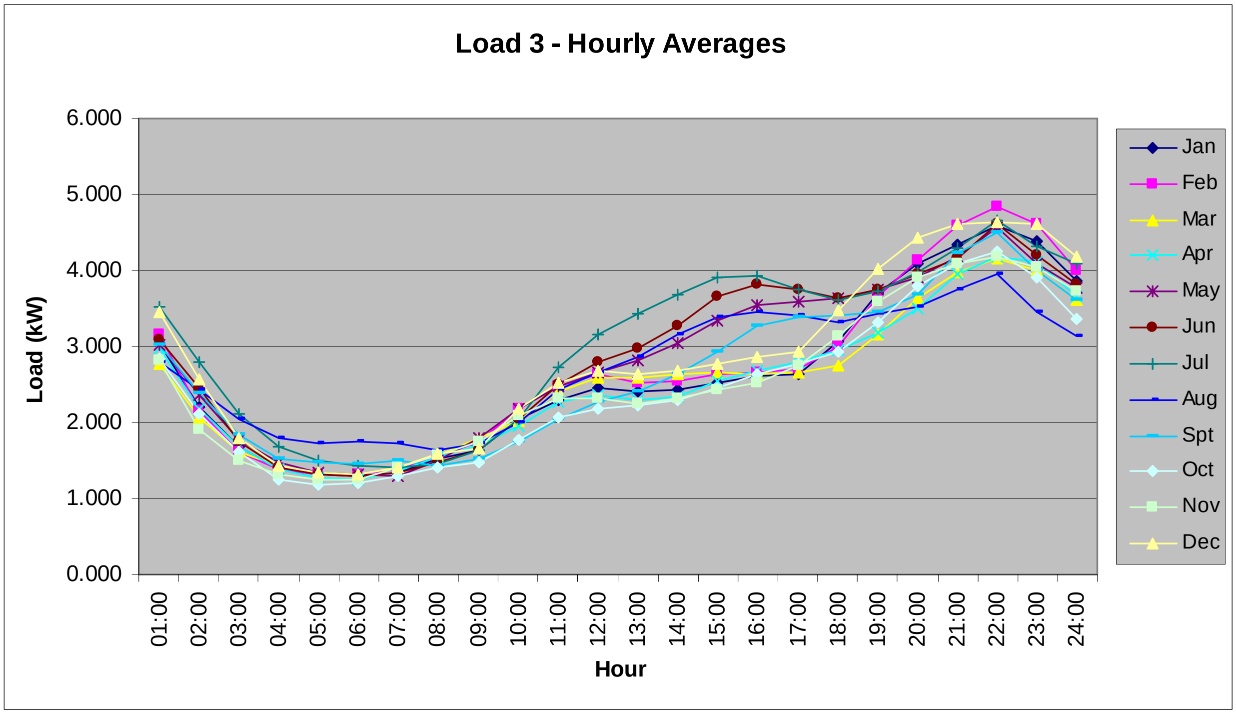

Figure 5.14: Daily Load Profile; Residence 3

Electric Rates

The dispatches that are created by the IDDRR algorithm designed in Chapter 4 depend heavily on the electric rate in place. For instance, with a net-metering rate structure in place where the customer can sell energy back at the same rate as he or she purchases energy, the battery, and therefore the dispatching algorithm, is unnecessary as the grid could be used as a 100% efficient battery from the customer's point of view. On the other hand, a rate structure in which energy rates are much higher during peak load hours could justify the cost of adding a distributed generation / distributed ESD system with a dispatching algorithm. For these case studies, 5 rate structures are implemented to find the effect of each.

All of these rate structures are, at least to some degree, based on the rates currently offered by Westar Energy. The actual cost of energy seen on an electric bill is much more complicated than simply 8 cents per kWh. It includes several line items that can vary depending on location and time of year and includes charges that are both dependent and independent of total energy usage [45]. To simplify this, it is assumed that a linear rate of \$0.092/kWh represents a typical Westar rate. The rate at which Westar purchases energy from the customer is also quite complicated, involving items such as the estimated cost of nuclear fuel burned [46], among other things. However, this can be simplified as roughly 150% of the avoided fuel cost. Based on a sample bill [45], the cost at which Westar would purchase energy from customers is about $0.036/kWh.

Rate 1 – No Net Metering, Static Rates

Rate 1 is modeled after the current rate system in Kansas using rate data from Westar Energy mentioned previously. It is intended to show how the dispatching algorithm performs with an "as it is today" rate structure. The rate structure is shown below in Figure 5.15.

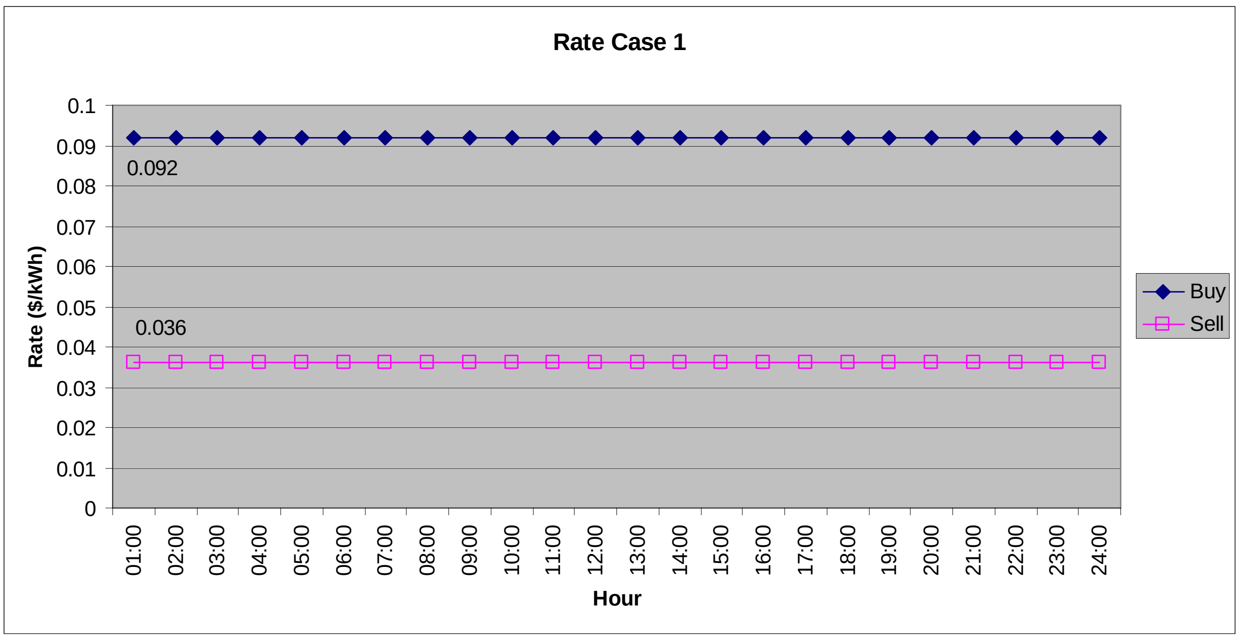

Figure 5.15: Rate Structure 1

Rate 2 – Net Metering, Static Rates

Rate 2 is a net-metering rate structure, which is becoming more common throughout the country and is a fiercely debated topic among electric providers and customers alike. In this net metering rate, the rates do not change throughout the day, i.e. there is no TOD pricing. Net metering is currently done in several different ways. Some electric providers compute the amount sold back to the utility versus the amount sold to the customer at the end of the month when the electric bills go out, while some may do it at the end of the year and then reimburse the customer [47]. For these case studies, net metering is done on an hour by hour basis, since the dispatch works on an hour by hour system. This rate structure is shown in Figure 5.16.

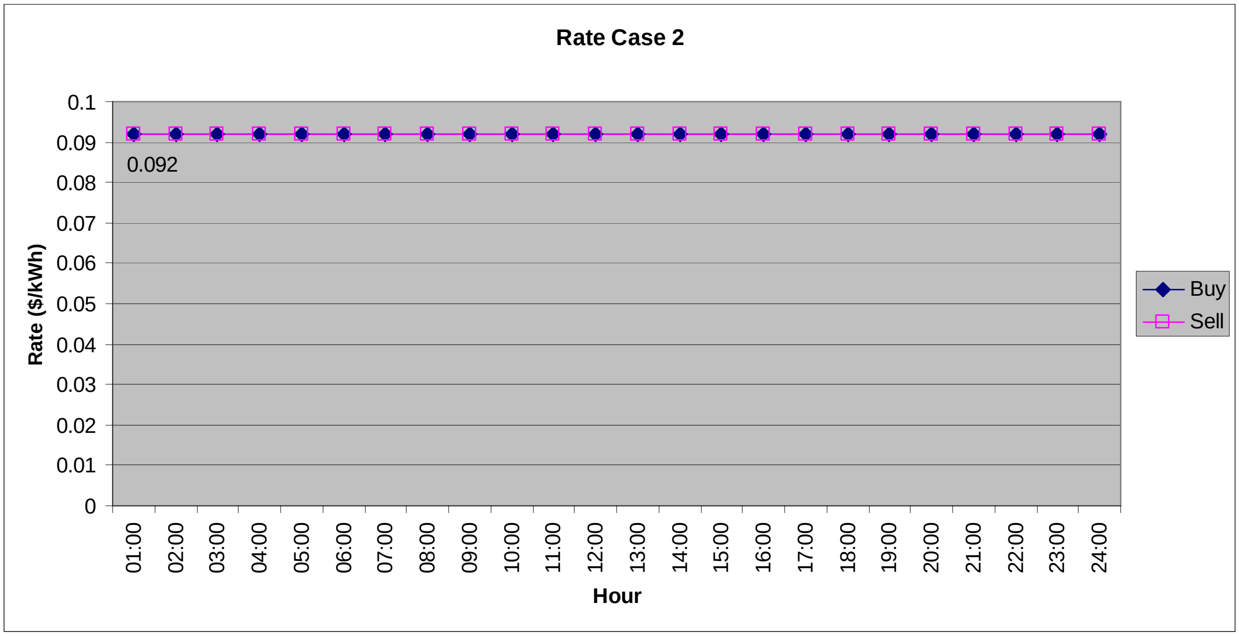

Figure 5.16: Rate Structure 2

It is expected that the battery should never be cycled under a net metering rate structure in which the rates never change, since the system can actually use the grid like an ideal ESD rather than using a battery with real inefficiencies.

Rate 3 – Net Metering, Dynamic Rates

Rate 3 is also a net metering rate, however TOD pricing is also included, unlike Rate 2. Under this rate structure, hourly net-metering would be in effect so that in any given hour the selling price is equal to the purchasing price, but the rates increase during peak periods. However, this type of rate structure in reality would most likely only be offered during peak months such as July and August. This rate structure is shown in Figure 5.17.

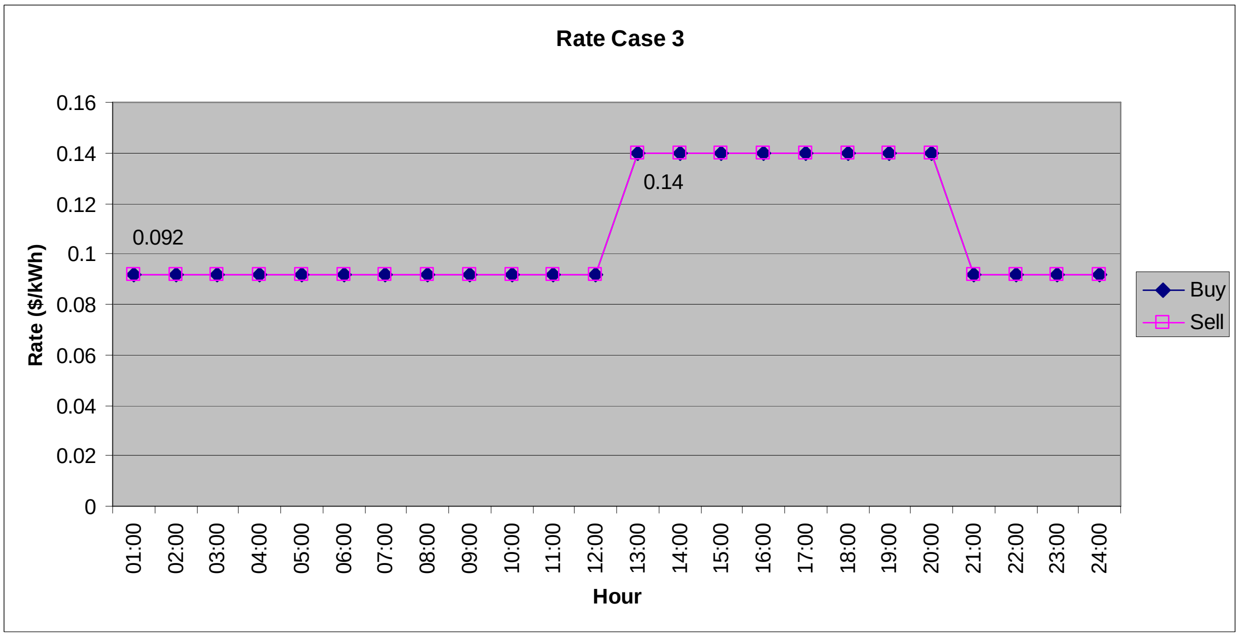

Figure 5.17: Rate Structure 3

Rate 4 – Emergency Metering 1, Dynamic Rates

Rate 4 is an emergency metering rate structure that also includes TOD pricing in the selling price, but not in the purchasing price. With this rate structure, the selling price is actually higher than the purchasing price during the peak hours from noon to 8:00 p.m. The utility could actually be losing money under this rate structure, but it may be offered in emergency situations when the electric provider cannot meet demand. In a situation like this nowadays, the utility would be forced to purchase energy from other providers on the spot market, shed load, or most likely some combination of the two, both of which can be extremely expensive. Of course these rates would typically only be offered occasionally and in the peak months, which would be July and August in Kansas. This rate structure is shown in Figure 5.18.

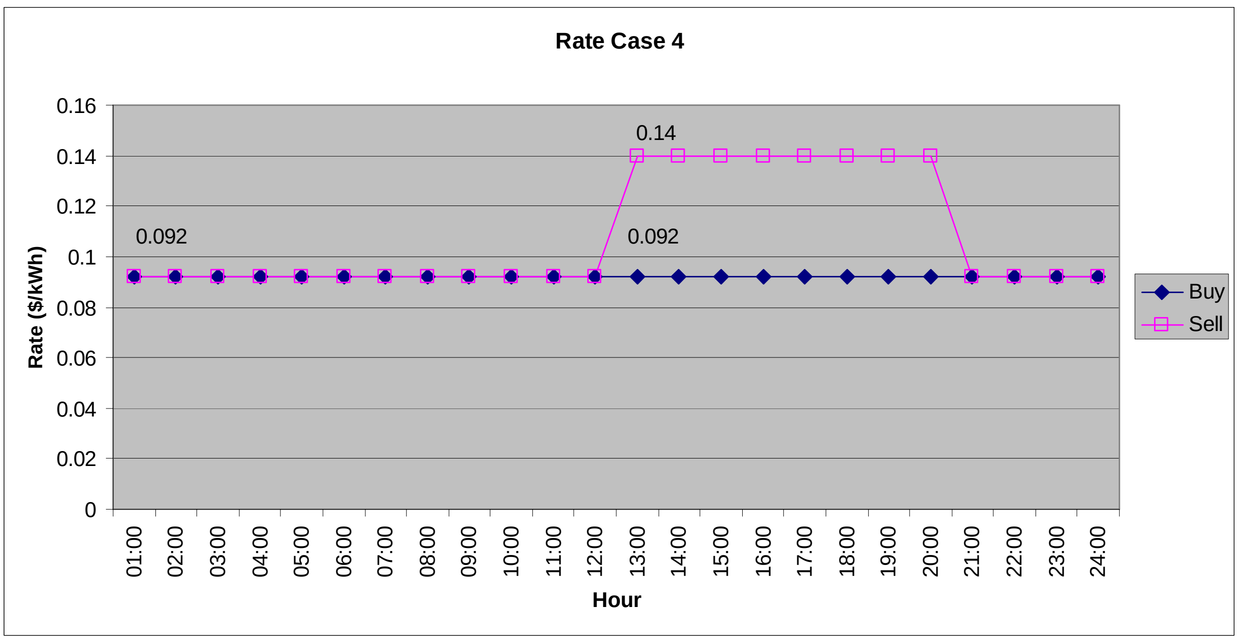

Figure 5.18: Rate Structure 4

Rate 5 – Emergency Metering 2, Dynamic Rates

Rate 5 is also an emergency metering rate structure. This rate case, shown in Figure 5.19, is similar to that of Rate 4, but with Rate 5 the purchasing rate is also slightly increased during the peak hours. This is also considered to be an emergency rate case since the utility would be loosing money during the peak hours, and therefore would only be implemented during the peak months of July and August.

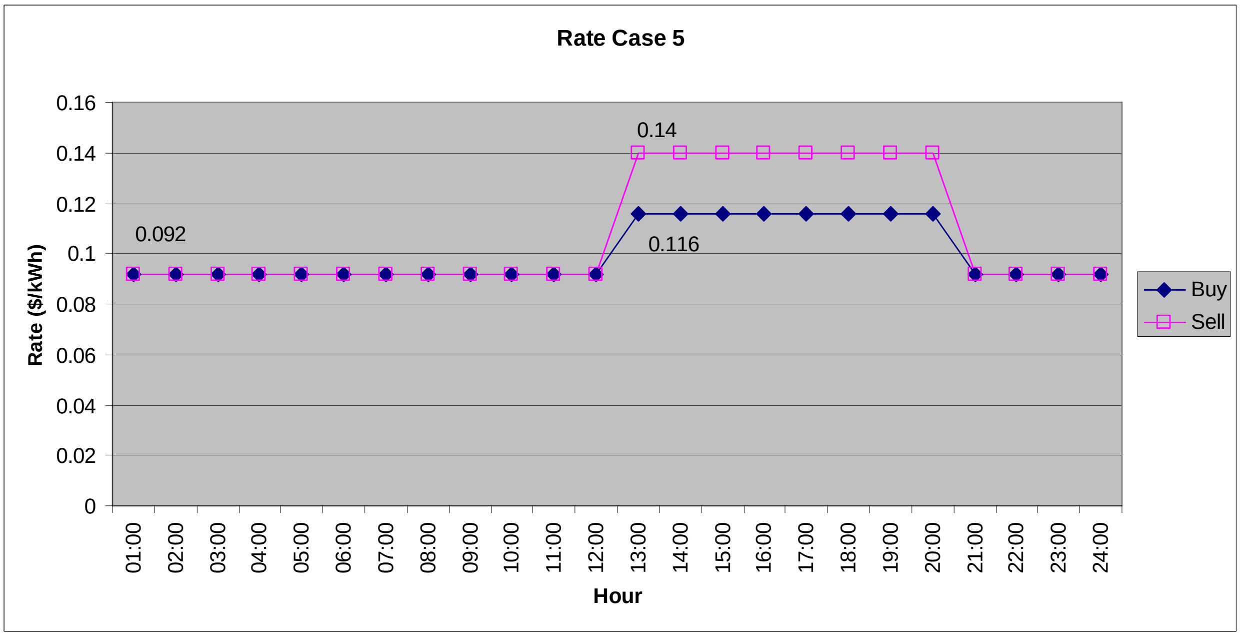

Figure 5.19: Rate Structure 5

Cost Incentives

In addition to the installation cost and replacement cost of batteries for each of the systems studied, there are renewable energy cost incentives that should be added to the total cost of the system when performing economic analysis. A summary of these incentives, both state and federal, is available online [48]. The biggest cost incentive for residents of Kansas is actually a 30% tax credit for wind and solar residential generators offered, not through the state, but by the federal government. So the cost of the system is effectively reduced to 70% immediately. Some states, such as California, offer many financial incentives programs, but unfortunately in Kansas, these only come in the form of loans and property tax exemptions (i.e. a person's property tax does not increase by adding a renewable energy system), which does not lower the installed cost of the system.

Single Day Simulations

These simulations test the dispatching algorithm on a variety of electric rates and renewable generators supported by an ESD. All of these case studies involve 24-hour-long simulations with one-hour dispatching periods. Case Studies 1 through 3 test the dispatching algorithm on real systems with two wind turbines and one solar system. Additional case studies seek to further the research based on what is found in Case Studies 1, 2 and 3. For each of these simulations, the battery is initially set to its minimum allowable discharge limit.

Case Study 0 – General Simulation

The purpose of this simulation is to implement the algorithm with real component values and catch any problems that may have been overlooked when developing the algorithm with unrealistic system characteristics. This case study does not go into any detailed economic analysis though, since it is still a fabricated system.

System

The system for Case Study 0 is a Skystream 3.7 wind turbine atop a 70' tower, connected to Load 1, with the ESD constraints given below in Table 5.6 that are based on typical numbers found throughout the research done for Chapter 2.

Table 5.6: System Constraints, Case Study 0

Maximum ESD Capacity (kWh)	3.78
Minimum Discharge Level (kWh)	0.756
Maximum Charging per Hour (kWh)	1.26
Maximum Discharging per Hour (kWh)	1.26
Charging Efficiency (%)	83
Discharging Efficiency (%)	83
Cycling Cost ($/cycle)	0.378

Results

Since this case study is just to show that the algorithm works with realistic constraints, only the month of June is shown. June was chosen because it offers a good mix of load and renewable generation. The load and resource profile along with the difference between the two is shown below in Figure 5.20. By looking at the difference between the two it can easily be seen that there is excess generation between the hours of 9 a.m. and 6 p.m.

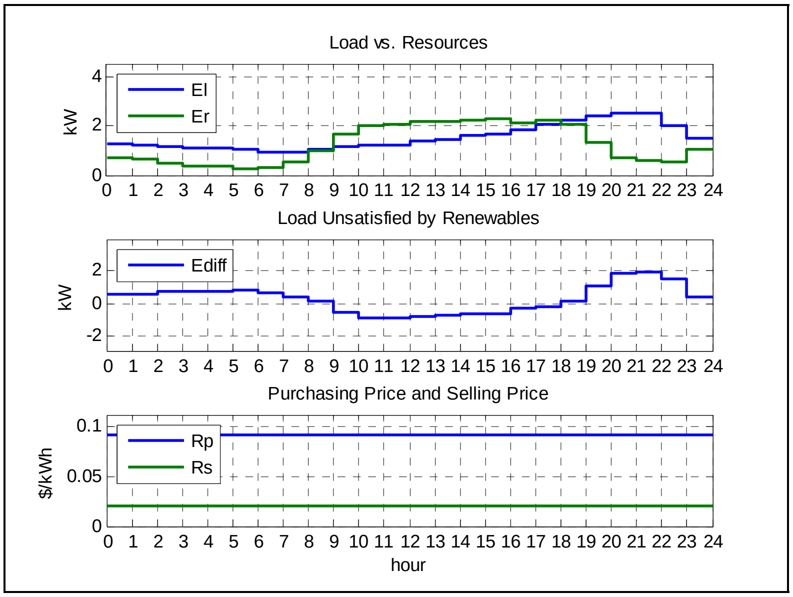

Figure 5.20: Load, Resources, and Rates; Case Study 0

The dispatch for this schedule, shown in Figure 5.21, is less than impressive. The battery is never cycled despite the fact that energy could be stored in the battery when there is excess generation and used to cut load. This would effectively make the energy in that time worth $0.092/kWh rather than $0.036/kWh as it is used in the dispatch in Figure 5.21.

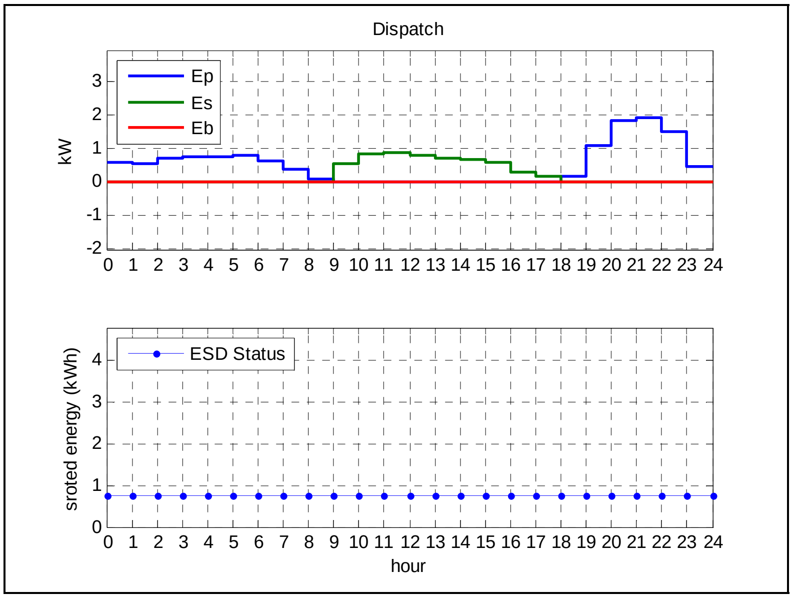

Figure 5.21: Dispatch Schedule; Case 0, Rate 1

This problem remains through all rate cases and the only time the battery is ever cycled is with Rate 4, see Figure 5.22, in which the selling price is much higher than the purchasing price between noon and 8 p.m. Even under those conditions the battery is hardly cycled at all and does not even come close to its peak capacity, as seen in Figure 5.23.

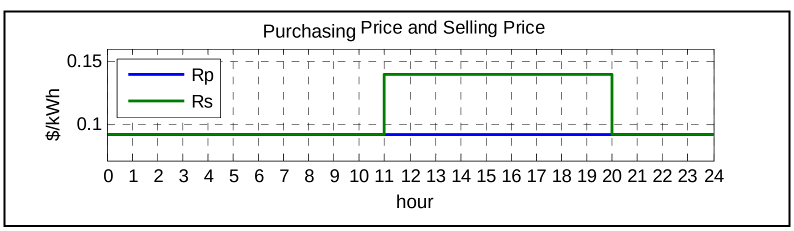

Figure 5.22: Rate 4

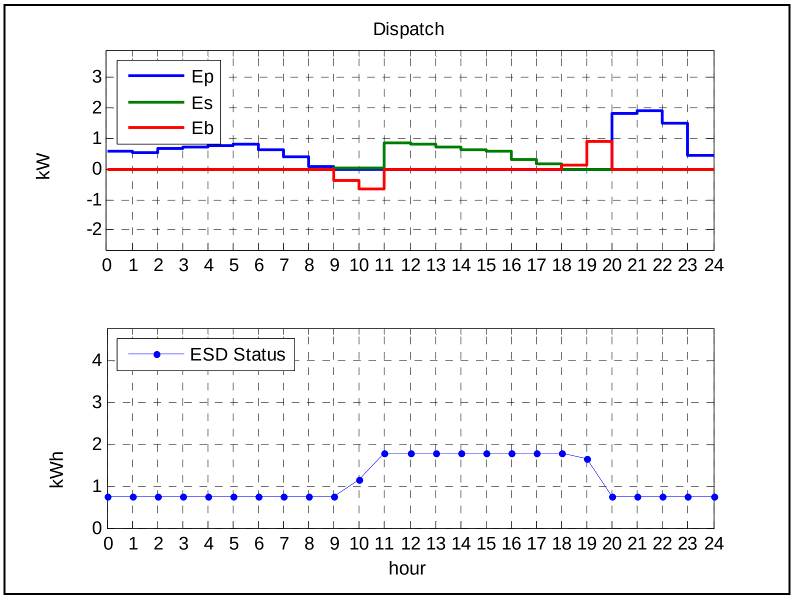

Figure 5.23: Dispatch Schedule; Case 0, Rate 4

Lessons Learned

This simulation has revealed an interesting fact. The battery is never cycled because the cycling cost, as it has been computed, is so high that it limits the system from ever using the battery. Remember from Chapter 4 that the cycling cost is defined as:

cycle cost = (cost of battery) / (number of expected cycles)

It can be shown that the cost of cycling the battery is actually higher than the energy would be worth if it was stored in the battery. For Case Study 0, the battery capacity is 3.78 kWh, but limited to 80% DOD, the battery has a usable capacity of 3.024 kWh. How much this amount of energy stored in a battery is worth depends on the cost at which the energy is attained and the cost at which it is used. Under these rates the best possible scenario is that the energy comes from the renewable generator, so it costs the customer nothing, and is sold back to the grid at the highest rate of $0.14/kWh. Under those conditions, and including charging and discharging efficiencies, the energy stored in the battery would be worth:

$$3.78\frac{kWh}{cycle}\times(0.83\times0.83)\left(.14\frac{\$}{kWh}-0\frac{\$}{kWh}\right)=0.365\frac{\$}{cycle}$$

The cost of cycling for this battery, on the other hand, is

$$\frac{\$567}{1500cycles}=0.378\frac{\$}{cycle}$$

So for this case study, it actually costs slightly more to cycle the battery than the amount of benefit that comes from doing so, and that is at the best possible charging and discharging costs. Reducing the cycling cost to 0.15 $/cycle gives the dispatch shown in Figure 5.24, and further reducing the cycling cost gives the same dispatch. It appears that battery cycling only occurs below a certain cycling cost threshold and after that it does not change.

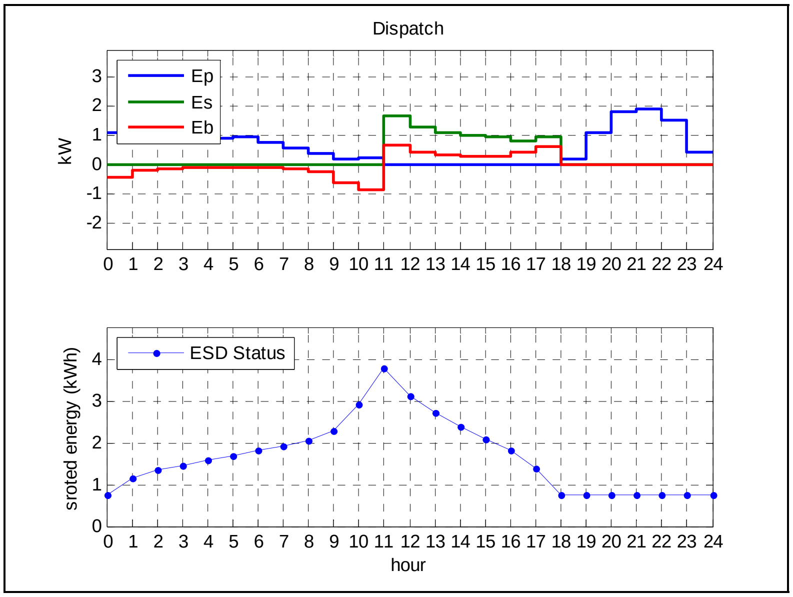

Figure 5.24: Dispatch Schedule; Case Study 0, Rate 4 with decreased cycle cost

For all additional case studies, cycling costs are set low enough to allow cycling regardless of the cost of the battery and number of cycles it is expected to complete over its lifetime. In order for the battery to cycle based on real numbers, one or more of the following would have to happen:

1. the cost of the battery would have to come down
2. the cycle life of the battery would have to increase
3. the electric rates would have to increase
4. the capacity of the battery would have to increase

Also, it must be understood that although the battery cycling cost is included in the cost equation of the LP, it is not considered in the present value calculations of the systems. Instead the cost of the battery and its periodic replacement based on usage is included in the present value calculations as shown in Appendix A.

Case Study 1 – Skystream 3.7, Load 1, Location 1

This is the first simulation involving completely real components, and is the first of three case studies to test how well the dispatching algorithm works with the renewable generators addressed in Chapter 2. These first three case studies likely dictate what additional case studies are needed.

System

This system is based around a Skystream 3.7 on at 70' pole serving Load 1 and located just outside of Manhattan. The assumed cost of installing the wind turbine portion of the system, minus the federal tax credit of 30%, is $10,500.

The average load for Load 1 between the hours of noon and 8 p.m., the peak hours, is 10.68kWh. So, the battery is sized to shift roughly 10.68kW of load from the peak hours to the off peak hours. A flooded type battery is used since it is the most common. The cheapest per kWh flooded battery is the Trojan T105 at 1110Wh for $130. This is a deep-cycle battery, but should be kept above 20% SOC, effectively reducing the battery's useful capacity to 888Wh. 12 T105 batteries allow enough capacity to nearly meet the average amount of energy used during the peak load hours, but since the T105 is a 6 volt battery and all the inverters researched are either 24 or 48 volt, the number of batteries has to be reduced to 8. This leaves about 7.104kWh of useful capacity. While this is not enough capacity to completely cover all of the peak demand, it is large enough to make a good dent. Also, an initial battery capacity can be taken into account, but for these simulations the initial amount is simply equal to the minimum amount that must be kept in the battery.

Since it is recommended that battery bank charging not exceed C/5 from 0 to 85% SOC and then be cut back to C/100 from then on, an average maximum charge rate of C/5.83 (1.52 kW) is enforced to linearize the charging schedule. Also, since the battery bank capacity being used is at the 5 hour rate, a maximum discharge rate of C/5 (1.77 kW) should not be exceeded.

The Outback GVFX2524 inverter is used since it most nearly matches the C/x rating of the battery bank at 1.32 kW, even if it is a bit lower. Fortunately, since the Skystream 3.7 already has an inverter built into it, the Outback system is really only needed for charging and discharging of the battery. This means the turbine can be connected to the AC bus and it does not matter that the combination of turbine power and battery power could exceed the overall rating of the inverter.

The efficiency of the battery is assumed to be a constant 85% and the efficiency of the inverter and charger is 91%. Since the efficiency reported for the battery is a round-trip efficiency, the efficiency one way is 92.2%. So the total discharging efficiency is:

$$(\textit{One way battery efficiency}) \times (\textit{inverter efficiency}) = .922 \times .91 = .839$$

and the total charging efficiency is:

$$(\textit{One way battery efficiency}) \times (\textit{inverter efficiency}) \times (\textit{charger efficiency}) = .922 \times .91 \times .92 = .764$$

Figure 5.25 illustrates how this system would be connected and Table 5.7 summarizes the constraints that are implemented in the dispatching algorithm for this system.

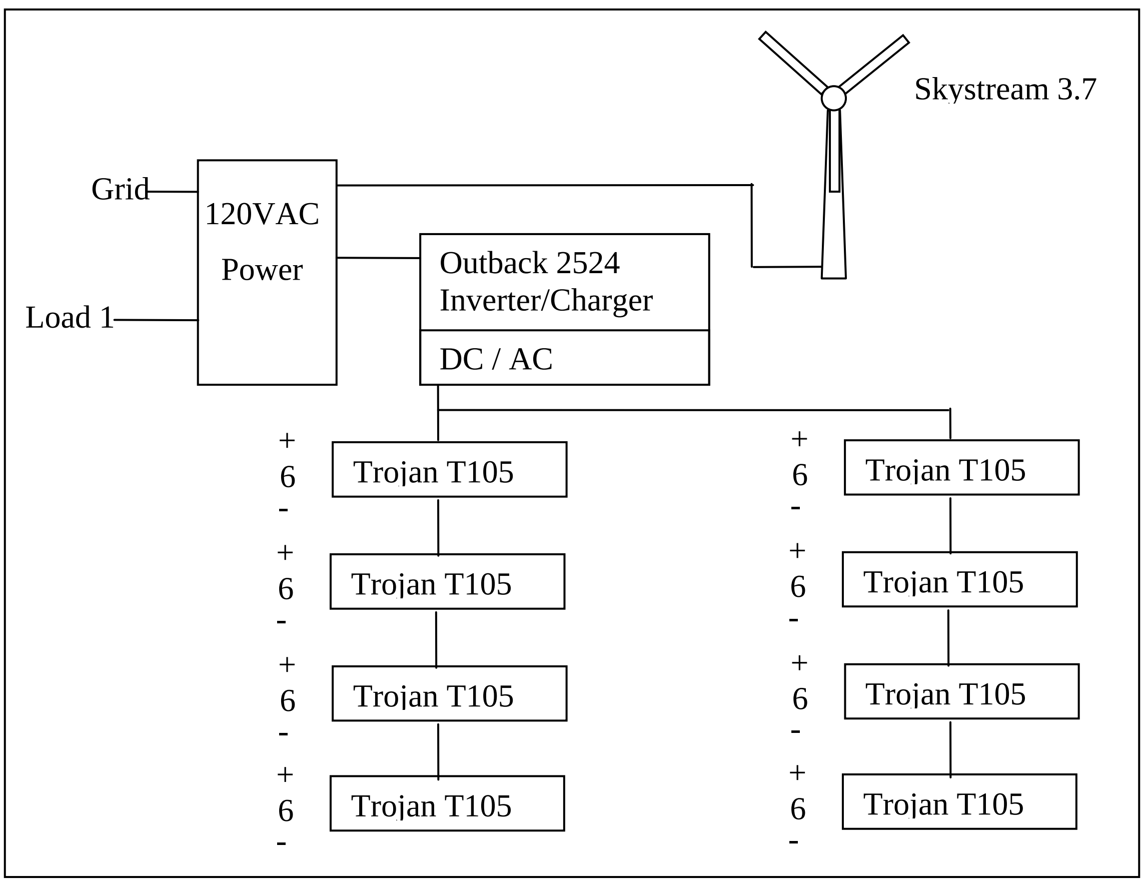

Figure 5.25: System, Case Study 1

Table 5.7: System Constraints, Case Study 1

Maximum ESD Capacity (kWh)	8.88
Minimum Discharge Level (kWh)	1.77
Maximum Charging per Hour (kWh)	1.32
Maximum Discharging per Hour (kWh)	1.77
Charging Efficiency (%)	76.4
Discharging Efficiency (%)	83.9
Cycling Cost ($/cycle)	0.01

Results

Energy production and economic feasibility results for the system in comparison to Rates 1 through 5 are given.

Rate 1

Even though the rates do not vary throughout the day with Rate 1, the algorithm is still useful since there are two different rates and therefore energy is worth different amounts depending on how it is used. Figures 5.26 and 5.27 show the resources, rates, and dispatch for the average day in May. By looking at the energy difference in Figure 5.26, it can be seen that excess energy is generated by the Skystream 3.7 wind turbine between the hours of 9 a.m. and 7 p.m. Rather than selling all of the energy back to the grid at a low rate, roughly half of it is stored in the battery system and used to cut the remaining load for the day that would have otherwise been purchased at the higher rate.

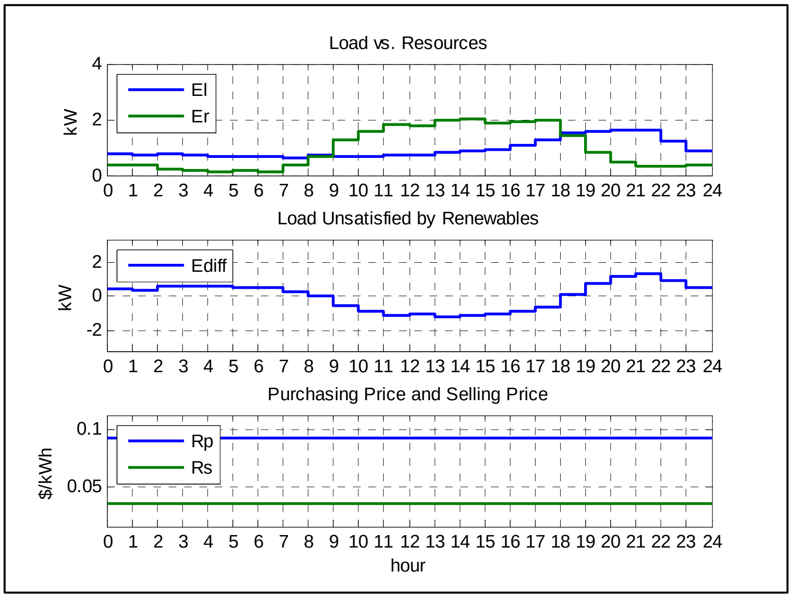

Figure 5.26: Load, Resources, and Rates, May Average

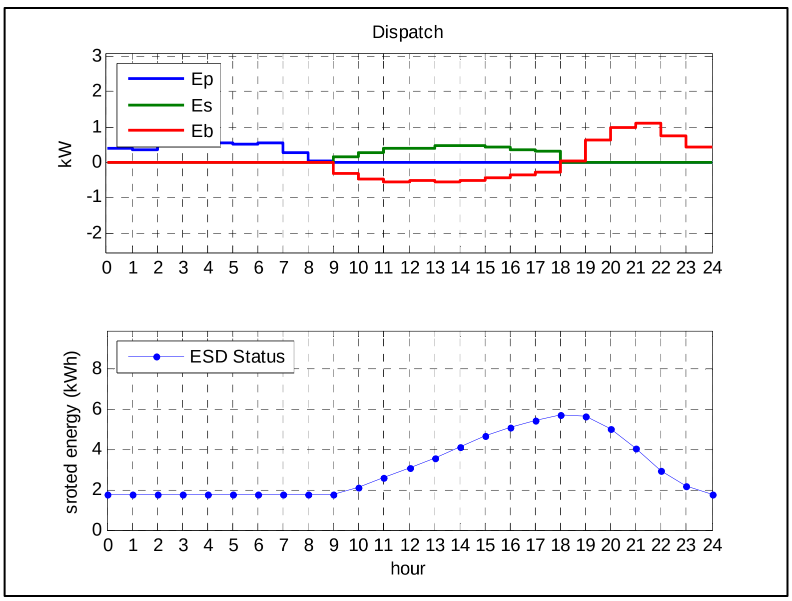

Figure 5.27: Dispatch Schedule for May

However, not all months have a dispatch schedule similar to that of May. Figures 5.28 and 5.29 show the load, resources, rates, and dispatch for July. It can be seen here that load is high enough that there is never excess energy production by the generator. Also, since the rates do not change and the selling rate is always lower than the purchasing rate; there is never any reason to store energy in the battery.

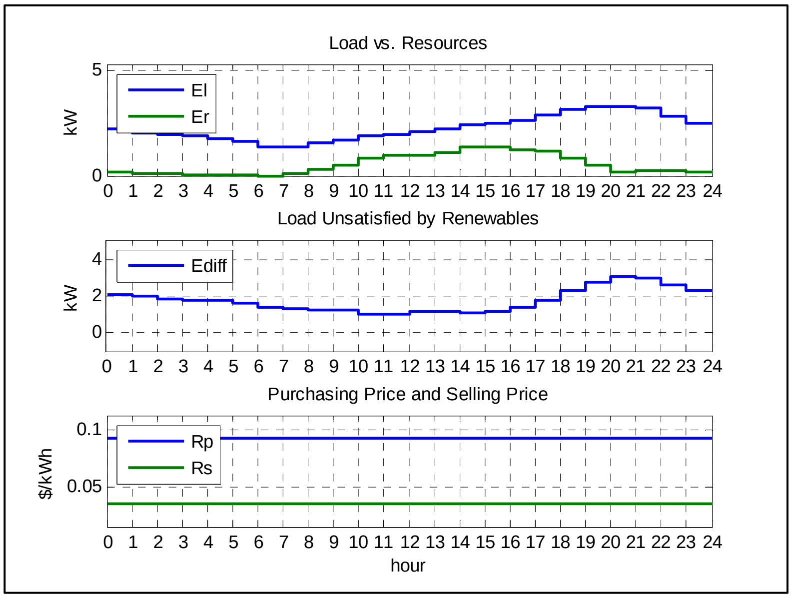

Figure 5.28: Load, Resources, and Rates, July Average

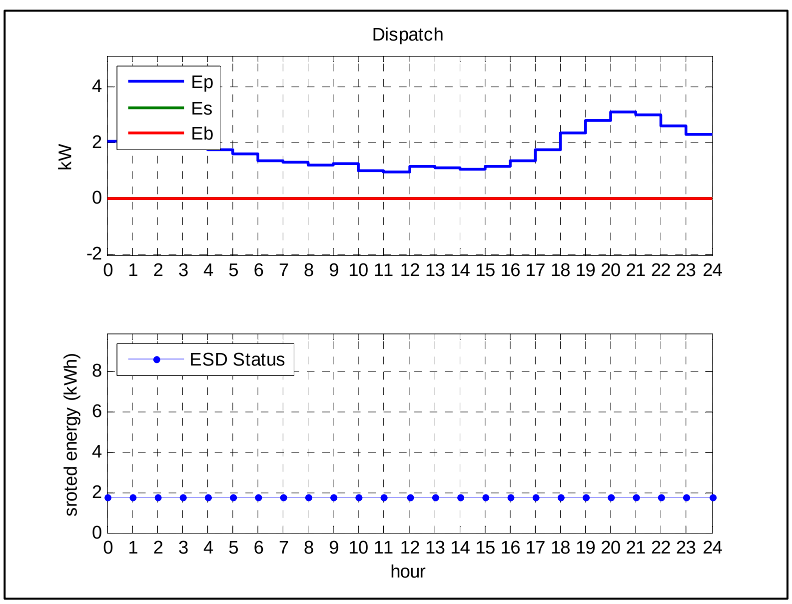

Figure 5.29: Dispatch Schedule for July

Table 5.8 summarizes the annual cost savings attributed to having a dispatchable ESD system in conjunction with the Skystream 3.7 turbine versus not having an ESD system and any type of renewable generator. It can be seen that having this system in place saves $532 per year versus not having a renewable generator and ESD system.

Table 5.8: Annual Savings with Dispatchable ESD System versus without ESD and Turbine, under Rate 1

Month	Daily Cost		Monthly Savings
	With Dispatchable ESD System	Without ESD and Turbine	
1	$0.63	$1.95	$40.97
2	$0.65	$1.99	$37.41
3	-$0.07	$1.80	$57.87
4	-$0.22	$1.78	$60.08
5	$0.23	$2.09	$57.72
6	$1.61	$3.39	$53.26
7	$3.85	$4.98	$35.08
8	$3.56	$4.57	$31.14
9	$1.58	$2.82	$37.24
10	$0.71	$2.00	$39.80
11	$0.38	$1.82	$43.23
12	$0.79	$2.01	$38.07
		Annual Savings	$531.87

Probably even more useful for comparison, Table 5.9 shows the annual savings of the system with a dispatchable ESD against a system that has only the Skystream wind turbine and no ESD system. When comparing these two systems, it only saves about $54 annually.

Table 5.9: Annual Savings with Dispatchable ESD System versus System without ESD, under Rate 1

Month	Daily Cost		Monthly Savings
	With Dispatchable ESD System	Without ESD	
1	$0.63	$0.82	$6.00
2	$0.65	$0.83	$4.98
3	-$0.07	$0.08	$4.63
4	-$0.22	-$0.08	$4.22
5	$0.23	$0.48	$7.65
6	$1.61	$1.64	$0.65
7	$3.85	$3.85	$0.00
8	$3.56	$3.56	$0.00
9	$1.58	$1.71	$3.71
10	$0.71	$0.93	$6.74
11	$0.38	$0.70	$9.55
12	$0.79	$0.97	$5.63
		Annual Savings	$53.75

Tables 5.8 and 5.9 are only annual savings though and do not include periodic costs such as battery replacement or account for the time value of money. To find if this system is really economically feasible, the initial cost of the system, the annual savings, and the replacement costs over the lifespan of the system (estimated at 20 years) must be compared in terms of Net Present Value (NPV). At the cycling rates of the ESD system under these energy cost rates, the batteries last just over 10 years with the cost of the replacement being $1,040 each time. With the initial cost of the Skystream 3.7, battery bank, and inverter estimated at $13,370, the total 20 year NPV of the wind turbine along with dispatchable ESD at an interest rate of 8% is a loss of $8,630 when compared to not having a turbine or battery system and simply paying for all energy directly from the grid. Also of interest, the 20 year NPV of a system without ESD, but with the Skystream generator is a loss of $5,806. Although the renewable generator by itself is still not economically justifiable, it does better than the system with a dispatchable battery by $2,824, despite the fact that it only saves $478 annually while the system with the dispatchable

ESD saves $532 each year. The difference comes from the initial and replacement costs of the battery system. The equations used to find the NPV are given in Appendix A.

Rate 2

As in Case Study 0, Rate 2 is much less interesting than Rate 1. Since the purchasing and selling price are equal and unchanged throughout the day, the system opts to sell all excess energy back to the grid rather than store it in the battery. Basically, the dispatching algorithm is using the grid as a lossless battery. Figures 5.30 and 5.31 show this occurrence.

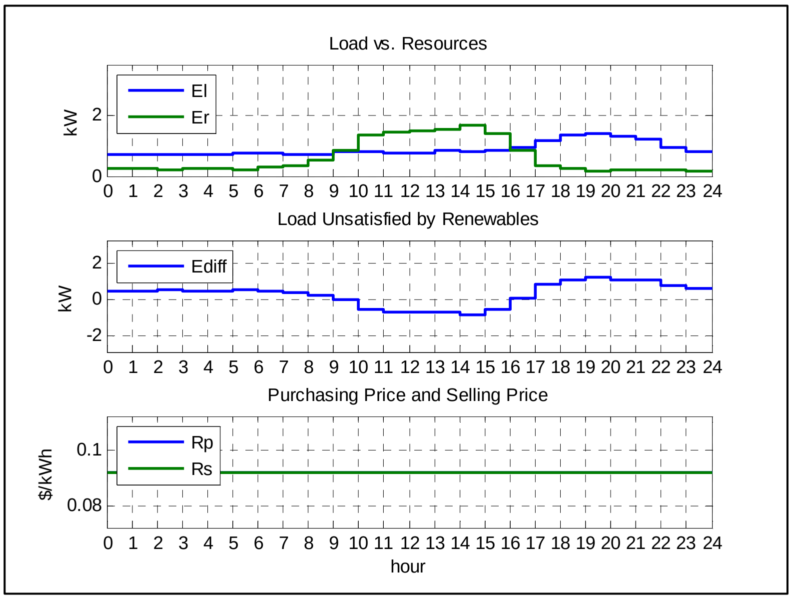

Figure 5.30: Load, Resources, and Rates, May Average

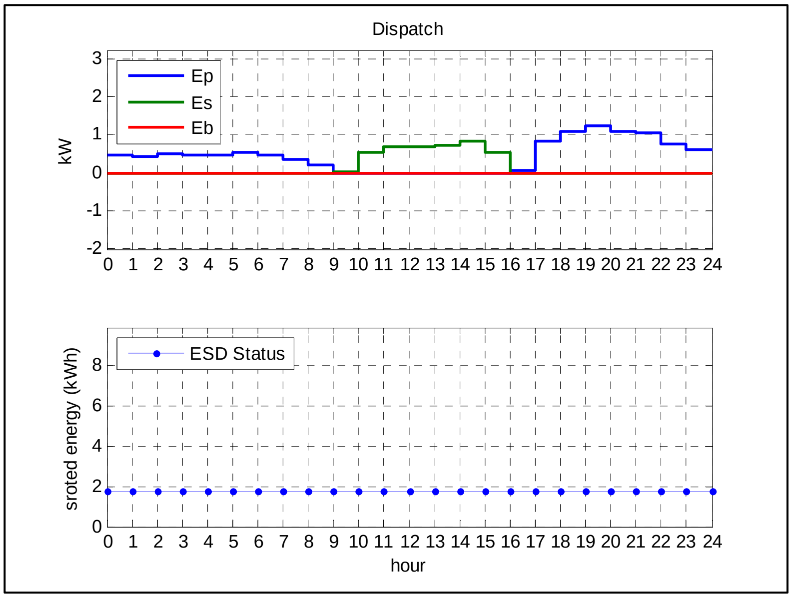

Figure 5.31: Dispatch Schedule for May

Even though the battery system is never utilized under Rate 2, it actually works out better economically than Rate 1, saving $579 per year for a 20 year NPV of negative $7,685. However, this should be expected since cost of energy under Rate 2 is always equal to or higher than in Rate 1 (9.2 cents/kWh buying and 3.6 cents/kWh selling under Rate 1, but always 9.2 cents/kWh under Rate 2).

Rate 1-3 and 2-3 Hybrids

These are combined rate structures coupling a normal off-peak rate, either Rate 1 or Rate 2, with a peak rate, Rate 3. Under these hybrid rate structures, Rate 3 is in effect only in the peak months of July and August. As shown previously, Rate 1 is a no net metering static rate, Rate 2 is a net metering static rate, and Rate 3 is a dynamic net metering rate used to help shave peak. It can be seen in Figures 5.32 and 5.33 that energy purchased from the grid during peak hours of July is nearly eliminated with Rate 3 in effect. August shows a nearly identical dispatch. Another interesting thing to note is that when Rate 3 is in effect, the system buys excess energy from the grid in the morning hours to help cover the peak since there is not enough production by the turbine to do so.

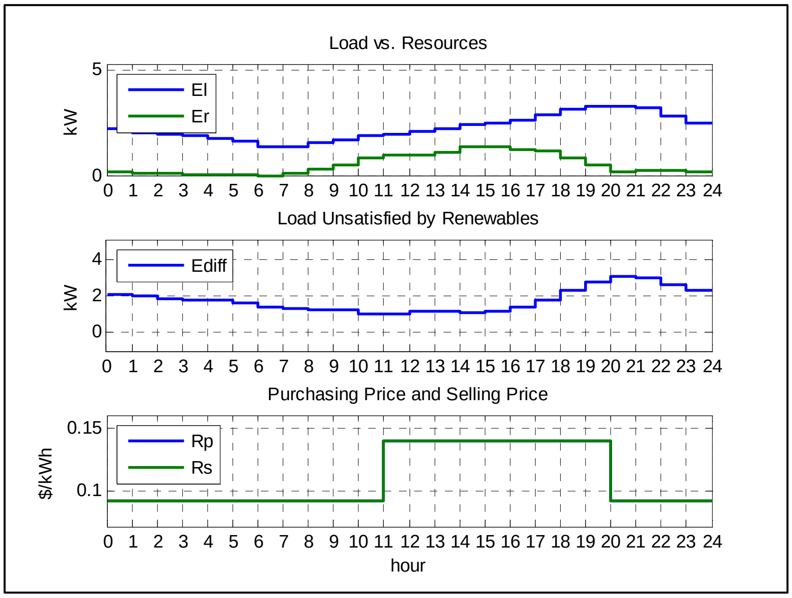

Figure 5.32: Load, Resources, and Rates, July Average

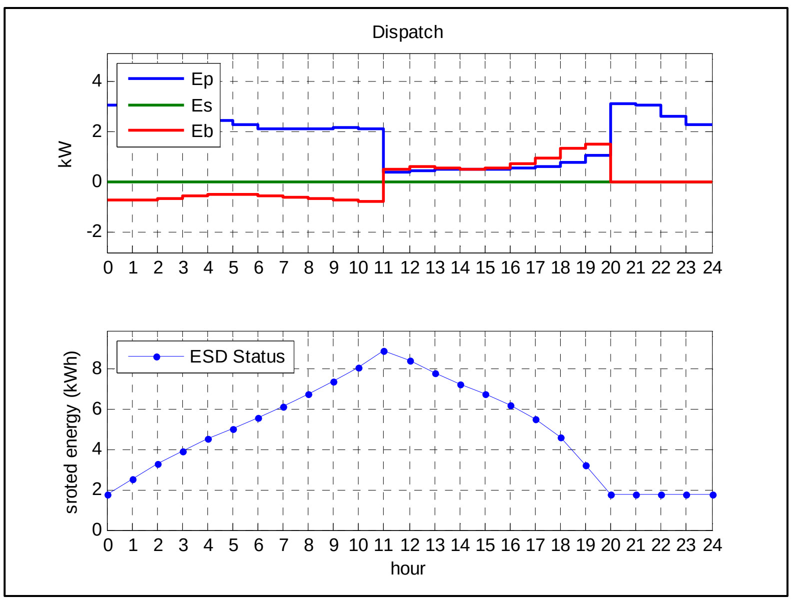

Figure 5.33: Dispatch Schedule for July

Unfortunately, the system is still not economically feasible for the owner of the system under either of the hybrid rates shown here. Under Rate 1-3 Hybrid, $622 is saved annually for a 20 year NPV of minus $8,223. Under Rate 2-3 Hybrid, $627 is saved each year in comparison to not having a generator and battery system. The 20 year NPV under this rate structure is still negative at minus $7,219.

Rate 1-4 and 2-4 Hybrids

Rate 4 is an emergency rate that would only be used when the utility cannot meet demand since the utility would most likely be losing money under this rate structure. However, it is possible that a rate like this could be offered to customers with dispatchable ESD systems in the peak months to help the utility meet demand. In those cases, Rate 4 does do a good job of both cutting and shifting peak load so that the utility does not have to generate or transmit as much as it would have to otherwise, as can be seen in Figures 5.34 and 5.35.

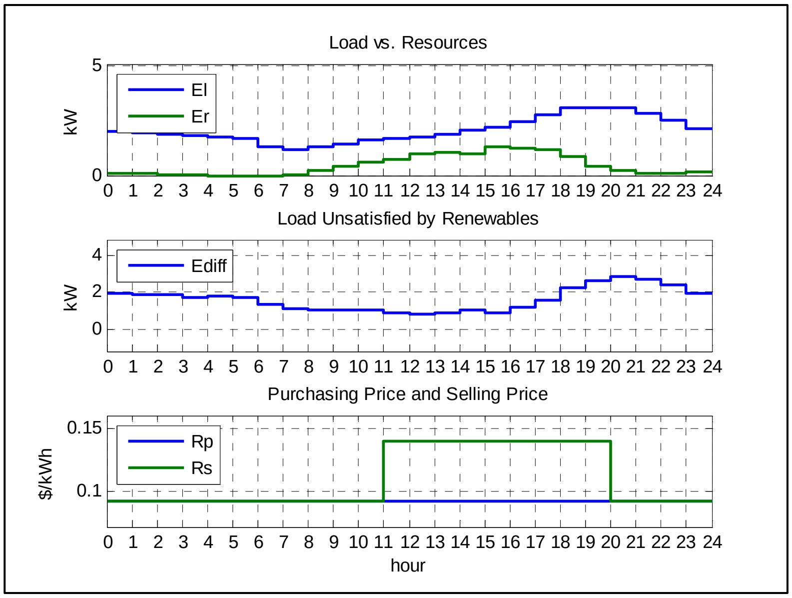

Figure 5.34: Load, Resources, and Rates, August Average

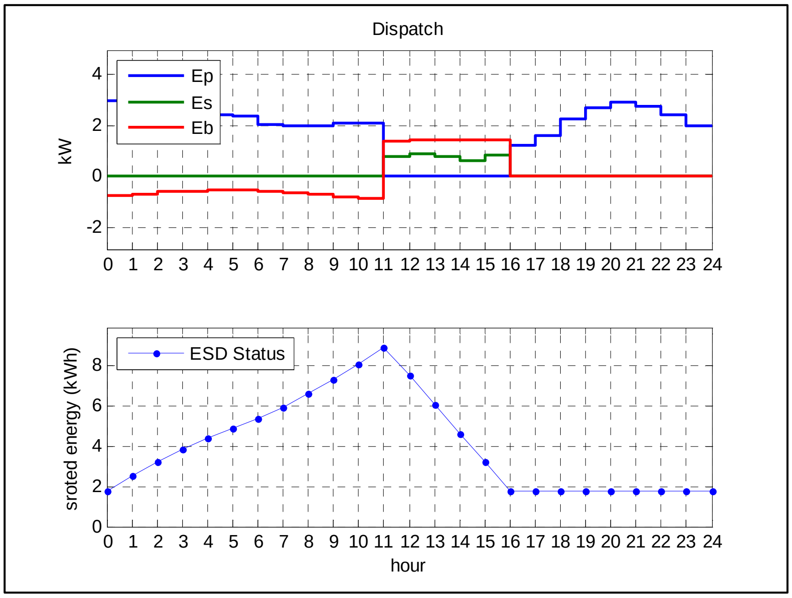

Figure 5.35: Dispatch Schedule for August

Under Rate 1-4 Hybrid, $580 is saved annually for a 20 year NPV of negative $8,634. Under Rate 2-4 Hybrid, the annual savings are $585 for a 20 year net present value of negative $7,630. So, even though the selling rate is higher than the purchasing rate during July and August, this rate schedule is actually worse for the owner of the system economically than the Rate 1-3 or Rate 2-3 Hybrid. Therefore, it still does not make economic sense to install the system.

Rate 1-5 and 2-5 Hybrids

Rate 5 is also an emergency rate, and as with the other dynamic rates, Rate 5 is able to lower peak demand during the peak months of July and August. In fact, the Rate 5 dispatch for July is very similar to the Rate 4 dispatch, however, there is more incentive to cut peak load with Rate 5 since the cost of purchasing energy increases, as seen in Figure 5.35. Accordingly, the dispatch opts to store slightly more energy than it would under Rate 4.

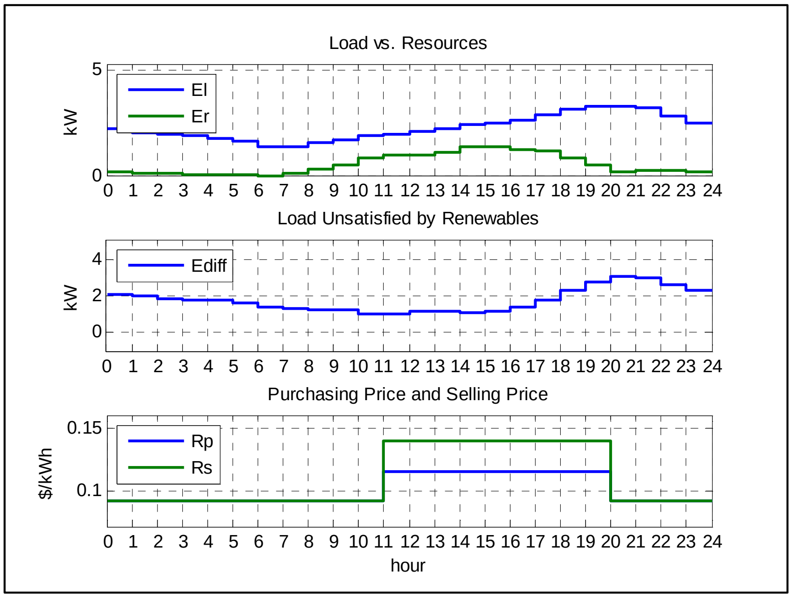

Figure 5.36: Load, Resources, and Rates; July Average

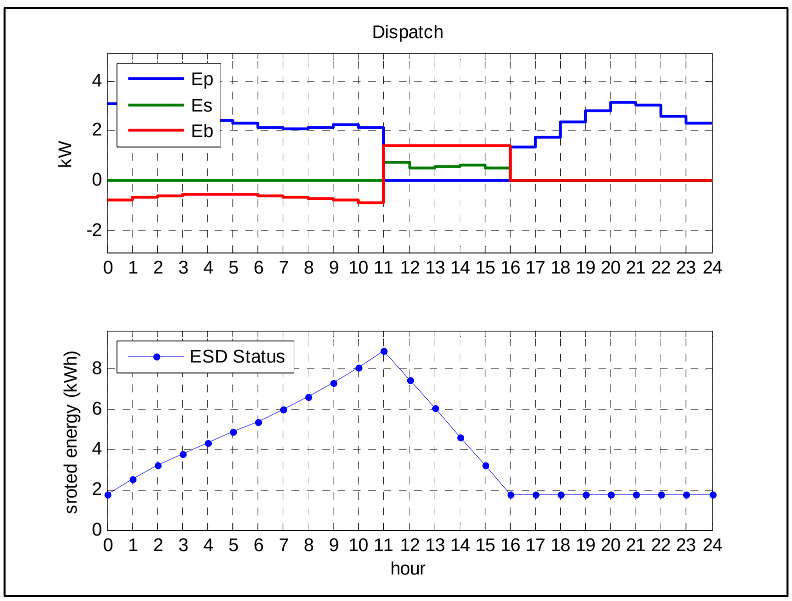

Figure 5.37: Dispatch Schedule for July

Under Rate 1-5 Hybrid, $601 is saved annually for a 20 year NPV of negative $8,428. Under Rate 2-5 Hybrid, $606 is saved annually for a 20 year NPV of $7,424.

Lessons Learned

Case Study 1 has shown that a customer-owned renewable energy system with dispatchable ESD based on the algorithm developed in Chapter 4 is capable of shifting load under certain rate cases, but is not economically feasible for the owner of the system under these rates as the initial cost of the system is still far from being recovered even after 20 years. In fact, from an economic standpoint, a system without ESD actually comes closer to breaking even due to the added initial cost of the battery system and replacement of the batteries associated with the dispatchable ESD system. However, this may change under higher rate cases where the economic potential of shifting energy is higher. The turbine/battery dispatchable system performed best under the Rate 2-3 hybrid, but does not break even after twenty years unless the installation cost can be reduced from an estimated $13,370 to about $6,150, either through increased state or federal financial incentives or by reduced materials/equipment or installation costs.

It was also shown that a dispatchable ESD system is unnecessary when coupled with Rate 2, since energy can be stored on the grid with no losses to the customer. Rate cases 1, 3, and 4 were all effective in shifting load but Rates 3 and 4 were much better at this. This is because with the unchanging prices of Rate 1, the system has no way to identify the peak hours.

Case Study 2 – Excel S, Load 1, Location 1

This case study is the second of three to investigate how well the dispatching algorithm works with real systems. For this case study, the system is a 10kW Bergey connected to the same load and in the same location as in Case Study 1 so that the results of two may be more easily compared.

System

Bergey, the company that manufactures the Excel S, offers several tower options, but only the 80’ tower is simulated here. Typical installed cost for an Excel-S varies from $48,000 to $65,000 [30]. The assumed cost of the installed system, including the 30% federal tax credit, is $42,420 including the battery system. Since this system is being simulated with the same load in Case Study 1, uses the same battery system and inverter. The constraints of this system are shown again in Table 5.10.

Table 5.10: System Constrains, Case Study 2

Maximum ESD Capacity (kWh)	8.88
Minimum Discharge Level (kWh)	1.77
Maximum Charging per Hour (kWh)	1.32
Maximum Discharging per Hour (kWh)	1.77
Charging Efficiency (%)	76.4
Discharging Efficiency (%)	83.9
Cycling Cost ($/cycle)	0.01

Results

Once again, results are shown for the same rate structures used in Case Study 1, however Rate 2 by itself has been omitted as it never uses the battery system.

Rate 1

Since the Excel-S is a 10 kW machine, the load is nearly or completely satisfied by the wind turbine in many of the months. For example, the load, resources, and dispatch for February, in which the load is almost completely covered, are shown in Figures 5.38 and 5.39. Because the load is taken care of by the turbine in many of the months, and because the rates are static, the battery cycled much less and not at all in some cases.

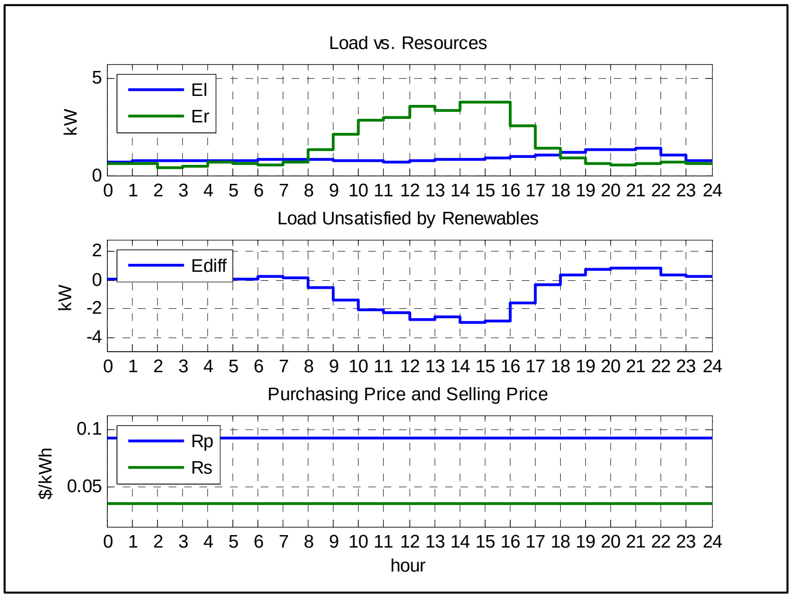

Figure 5.38: Load, Resources, and Rates; February Average

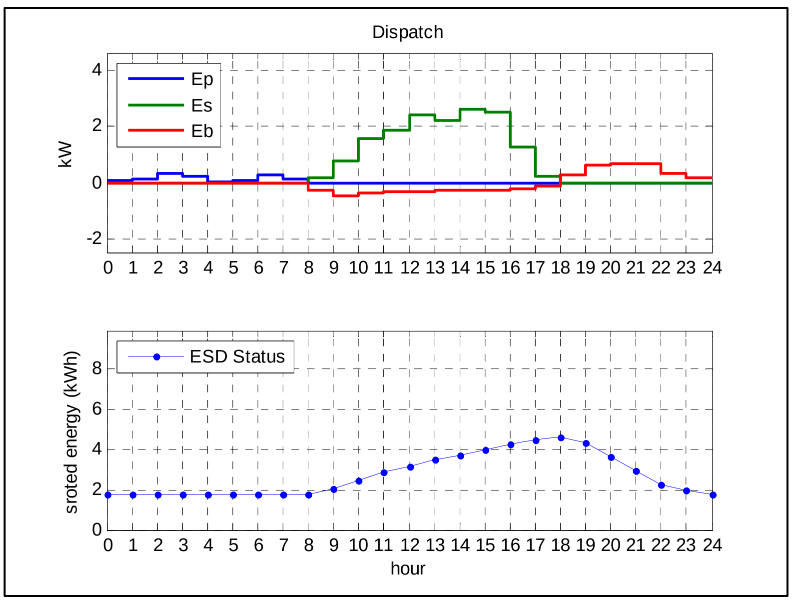

Figure 5.39: Dispatch Schedule for February

However, just like in Case Study 1, when there is load that is not satisfied by the turbine towards the end of the day, the battery is used to store some of the excess to cover that load. The rest of the excess is sold back immediately. Although the peak demand time is not specified by the rates, peak shaving naturally occurs due to the timing of when the turbine production drops off, which would be beneficial to a capacity-constrained electric provider. The month of September is a good example of this as shown in Figure 5.40 and 5.41.

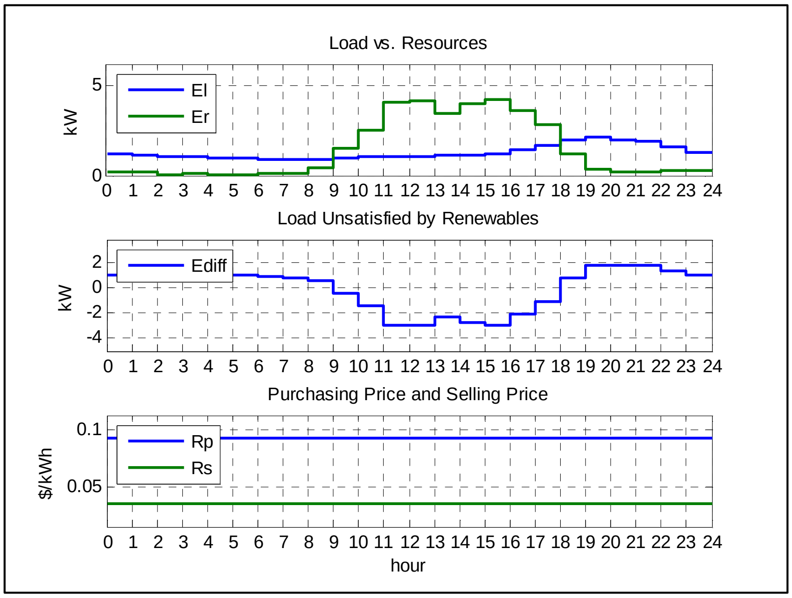

Figure 5.40: Load, Resources, and Rates; September Average

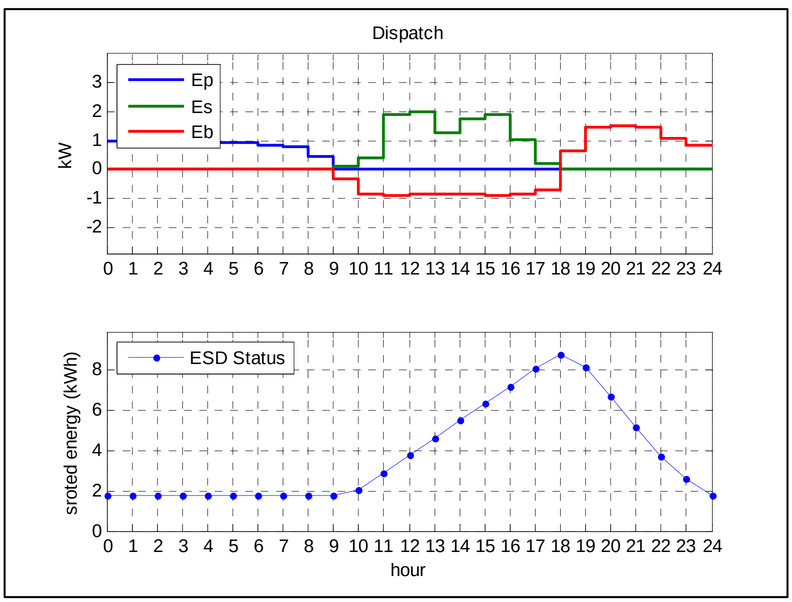

Figure 5.41: Dispatch Schedule for September

With this system in place under Rate 1, the owner of the system could expect to save $1,023 each year on electric usage versus having no generator and battery, but the costs associated with installing and operating the system, most notably the high cost of the turbine and tower, keep the system economically infeasible. When considering the cost savings of this system versus not having a renewable/battery system at all, the NPV of the system after 20 years is very poor at a negative $32,790.

Rate 2

Detailed results from this rate case have been omitted since the system never uses the battery, but the 20 year NPV under this rate case is negative $28,215.

Rate 1-3 and 2-3 Hybrid

As in Case Study 1 and as mentioned previously, the battery is never cycled under Rate 2 since the purchasing and selling prices are always equal and unchanging. Also as in Case Study 1, the system does a good job of peak shaving once Rate 3 comes into effect in the months of July and August. Had Rate 3 been in effect in all months, the system would not only able to completely eliminate the peak load, but would also able to sell a good deal of energy back to the grid and further help the utility meet demand. Figures 5.42 and 5.43 show the system cutting peak load in the month of August.

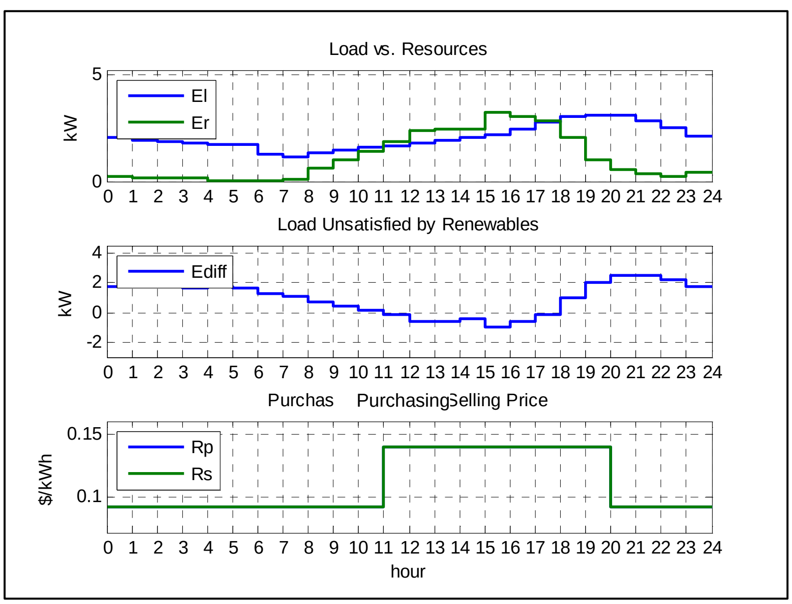

Figure 5.42: Load, Resources, and Rates; August Average

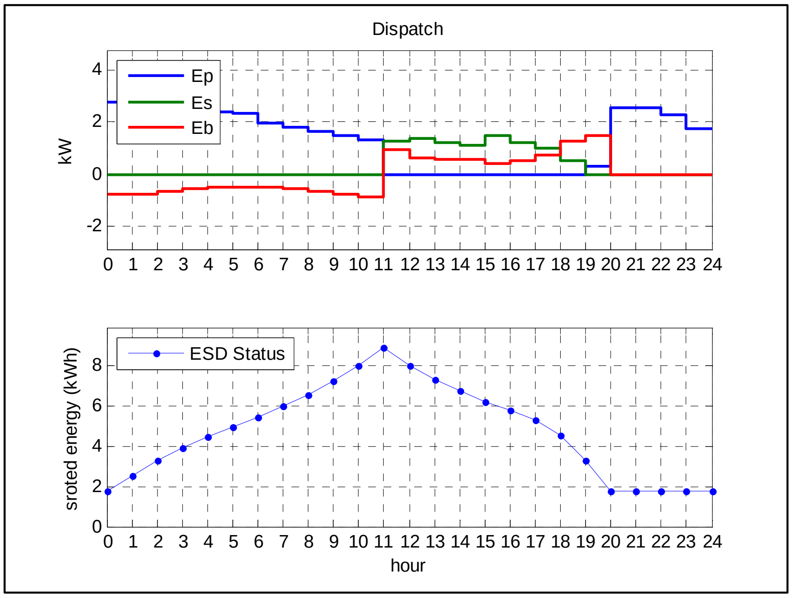

Figure 5.43: Dispatch Schedule for August

Under Rate 1-3 Hybrid, $1,111 is saved annually for a 20 NPV of negative $31,515. Under Rate 2-3 Hybrid, $1,533 is saved annually for a 20 year NPV of negative $27,369. So, while this rate structure is economically better for the owner than Rate 1 is, it is still not economically feasible.

Rate 1-4 and 2-4 Hybrid

The system under Rate 2-4 Hybrid performed very much as it did in Case Study 1. The load, resources, rates and dispatch schedule for July can be seen in Figures 5.44 and 5.45. In this month, excess energy is purchased from the grid during the morning hours. The stored energy is then sold back, along with the excess generation, during the peak time when the selling rate is higher than the buying rate.

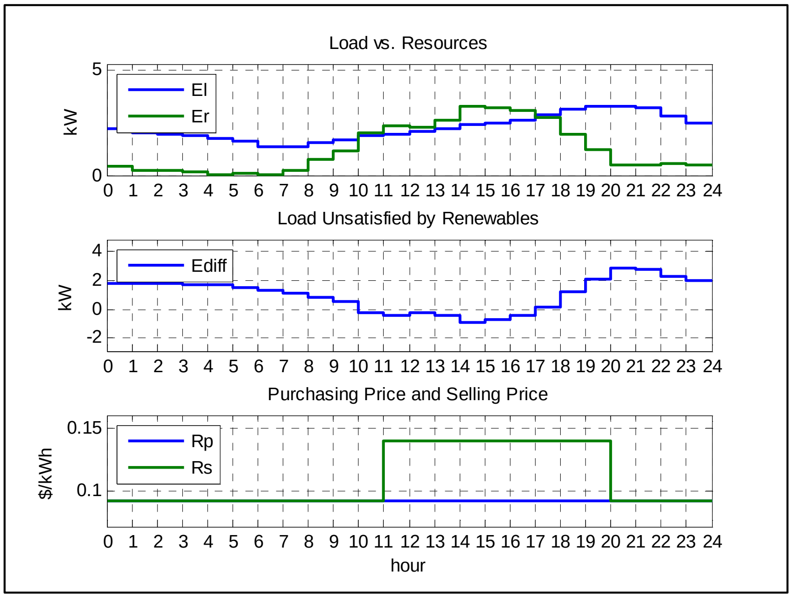

Figure 5.44: Load, Resources, and Rates; July Average

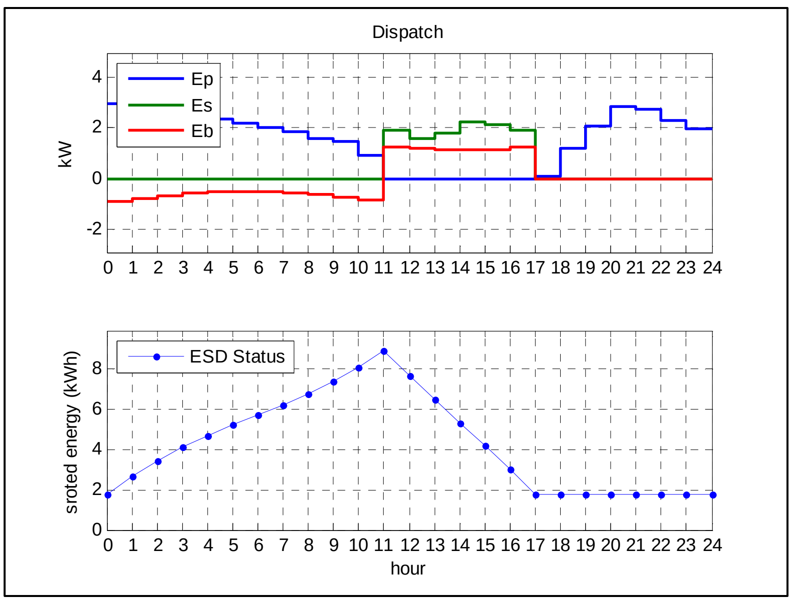

Figure 5.45: Dispatch Schedule for July

The system implemented in Case Study 2 saved $1,055 annually under Rate 1-4 Hybrid for a NPV of negative $32,064. $1,477 were saved annually under the Rate 2-4 Hybrid, slightly less than Rate 2-3 Hybrid, and of course was still not able to justify the costs of the system at a 20 year NPV of negative $27,918.

Rate 1-5 and 2-5 Hybrid

As in Case Study 1, Rate 5 is also able to help shave energy usage from the peak hours when it is in effect in the months of July and August. The load, resources, rates, and dispatch for August are shown in Figures 5.46 and 5.47. It can be seen that once again, the system stores excess energy from the grid so that it may cut load during the high purchasing time of the day and take advantage of the higher selling rate during the peak demand hours.

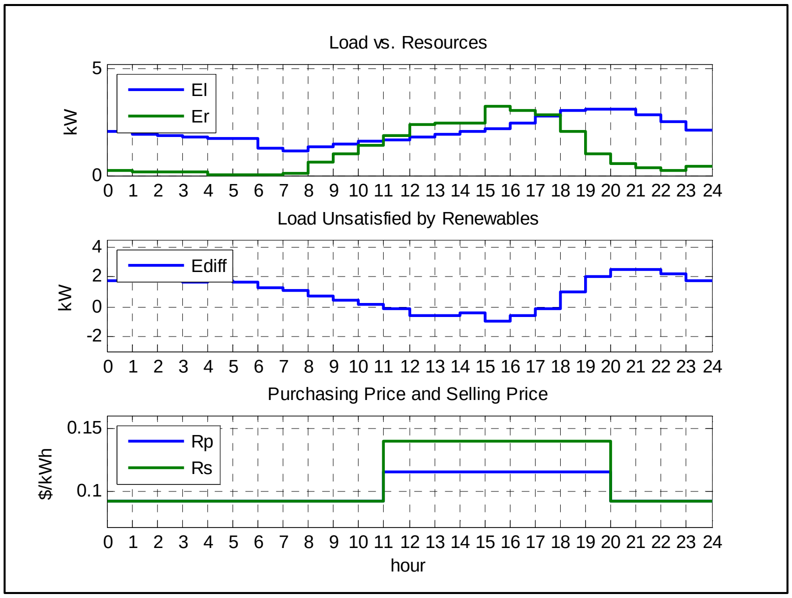

Figure 5.46: Load, Resources, and Rates; August Average

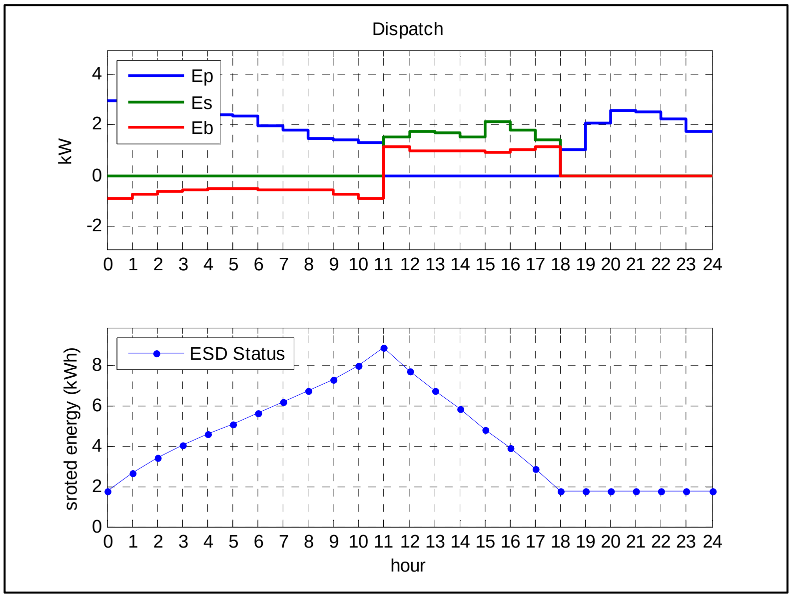

Figure 5.47: Dispatch Schedule for August

Under Rate 1-5 Hybrid, $1,083 is saved annually for a 20 year NPV of negative $31,789. Under Rate 2-4, $1505 is saved annually for a 20 year NPV of negative $27,644.

Lessons Learned

As in Case Study 1, the system worked well in shaving/shifting peak demand, especially under rate cases where the peak is well defined by an increase in electric rates. In many cases, the larger turbine worked better from the utility's point of view, providing more excess generation onto the grid during the peak times. However, the economic gain produced by this system is not enough to overcome the high initial cost of installing the system and the cost of periodically replacing the batteries. Like Case Study 1, the best rate from the customer's economic point of view proved to be Rate 2-3 Hybrid, but for the system to break even at 20 years, the installation cost would have to decrease from $42,420 to just about $15,000.

Case Study 3 – Solar System, Load 1, Location 1

The purpose of Case Study 3 is to investigate how well the dispatching algorithm works with a solar system, rather than a wind system as in Case Studies 1 and 2. It can be seen by looking at Figure 5.5 in the Solar Data Section and Figures 5.12, 5.13, and 5.14 in the Load Data section that peak solar production time does not line up with peak load as well as peak wind speeds do (Figures 5.1 and 5.3), which might make the dispatching algorithm more useful than with wind turbines. For the sake of comparison, Case Study 3 is also implemented with Load 1.

System

This solar system uses 14 SGT 160 solar panels, giving a total power rating of 2.24 kW. The cost of the power generation aspect of this system, taken from Figure 2.14, is $13,440 including the inverter and after the 30% tax credit. Once again, the same battery system is used as was used in Case Studies 1 and 2. Although the solar system already comes with an inverter, it is only sized for the solar panels; therefore the same inverter is used for the batteries as was used before. This means the system constraints, shown again in Table 5.11, also remain the same.

Table 5.11: System Constraints, Case Study 3

Maximum ESD Capacity (kWh)	8.88
Minimum Discharge Level (kWh)	1.77
Maximum Charging per Hour (kWh)	1.32
Maximum Discharging per Hour (kWh)	1.77
Charging Efficiency (%)	76.4
Discharging Efficiency (%)	83.9
Cycling Cost ($/cycle)	0.01

The amount of solar energy falling on a surface depends heavily on the angle of the surface relative to the sun. To optimize the system so that it produced the most during the entire year, the panels should be tilted to the same angle as the latitude of the site so that they are perpendicular with the sun during the solar equinox. The latitude of Manhattan, KS is about 39° N.

Results

Rate 1

For the Rate 1 case, the solar system is somewhat undersized and the battery is never fully charged. In the summer months, the solar system never produced excess energy and the batteries were not used at all. This dispatch for an average day in April is shown in Figures 5.48 and 5.49.

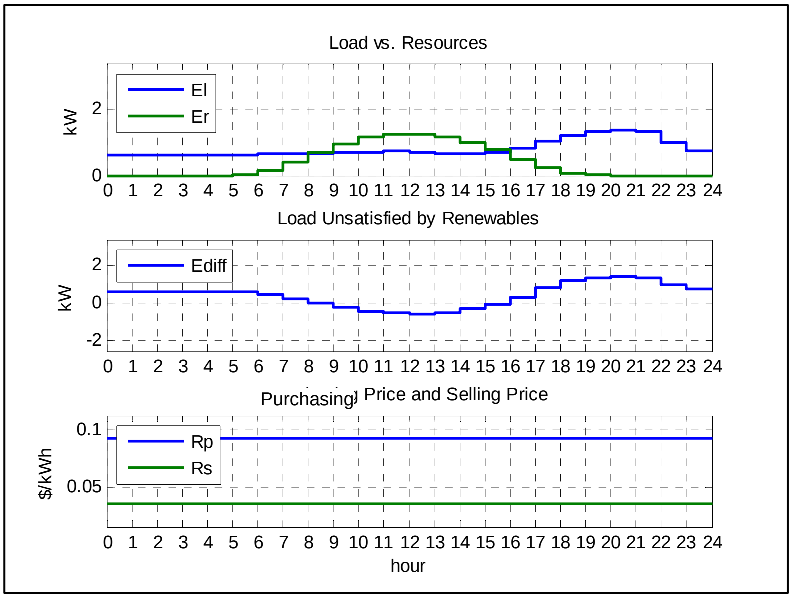

Figure 5.48: Load, Resources, and Rates; April Average

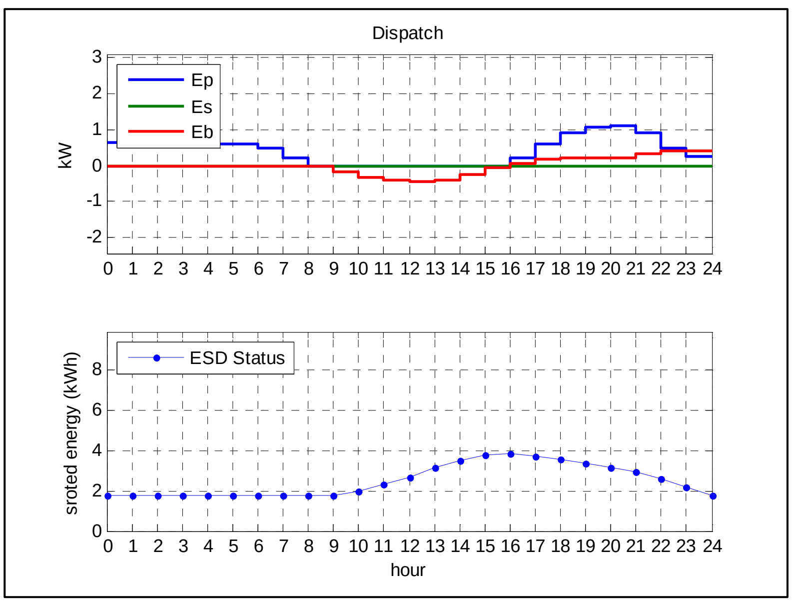

Figure 5.49: Dispatch Schedule for April

Compared to combining these rates with a system that has no solar panels or battery, the system saved about $291 per year. However, like the other systems already studied, the high initial cost lead to a negative 20 year NPV of minus $13,456.

Rate 2

Once again, the battery is not used during Rate 2, but for completeness the annual cost savings of $294 and 20 year NPV of negative $13,419 have been computed.

Rate 1-3 and 2-3 Hybrid

With Rate 3 implemented in July and August and either Rate 1or Rate 2 the rest of the year, the system saved $331 and $335 per year respectively, but had 20 year NPVs of negative $13,444 and negative $13,306, which is only slightly better than under a continuous year long Rate 1. As mentioned before, the battery is never used with Rate 2 in effect, but under Rate 3 the system is able to eliminate the peak load and sell back to the utility at that time. The load, resources, rates and dispatch schedule for August is shown in Figures 5.50 and 5.51.

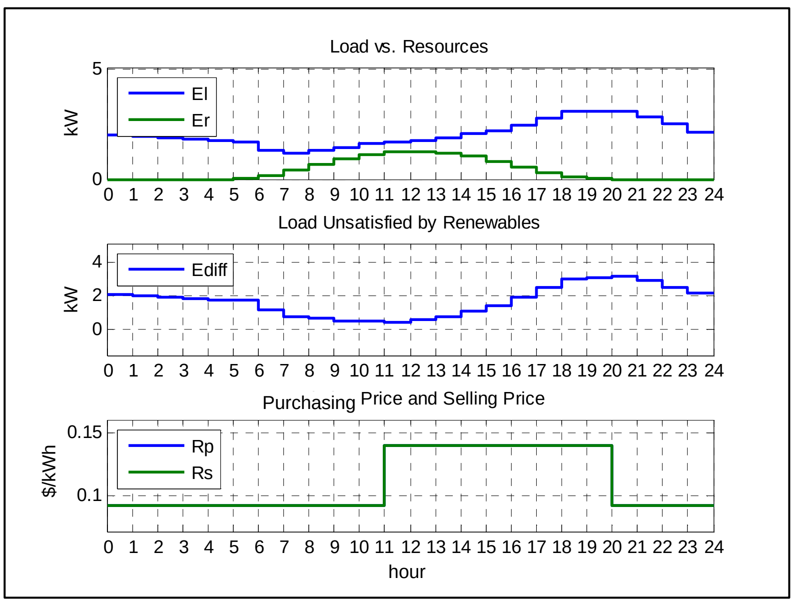

Figure 5.50: Load, Resources, and Rate; August Average

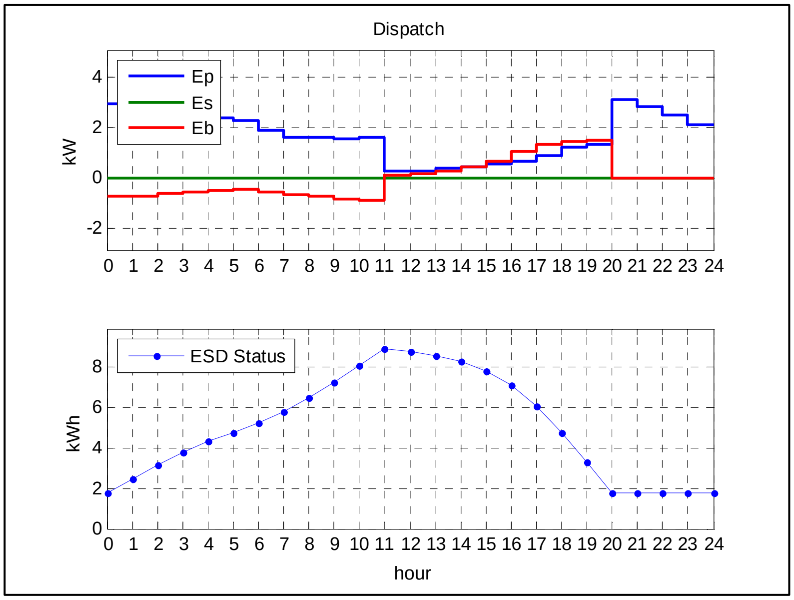

Figure 5.51: Dispatch Schedule for August

Rate 1-4 and 2-4 Hybrid

Under the 2-4 Hybrid Rate the system saved slightly less annually than Rate 2-3 at $302. However, once again the system cannot be justified economically due to a 20 year NPV of minus $13,348. Under Rate 1-4, the system is only able to save $298 per year for a 20 year NPV of negative $13,768. The inputs and dispatch for an average July day are shown in Figures 5.52 and 5.53.

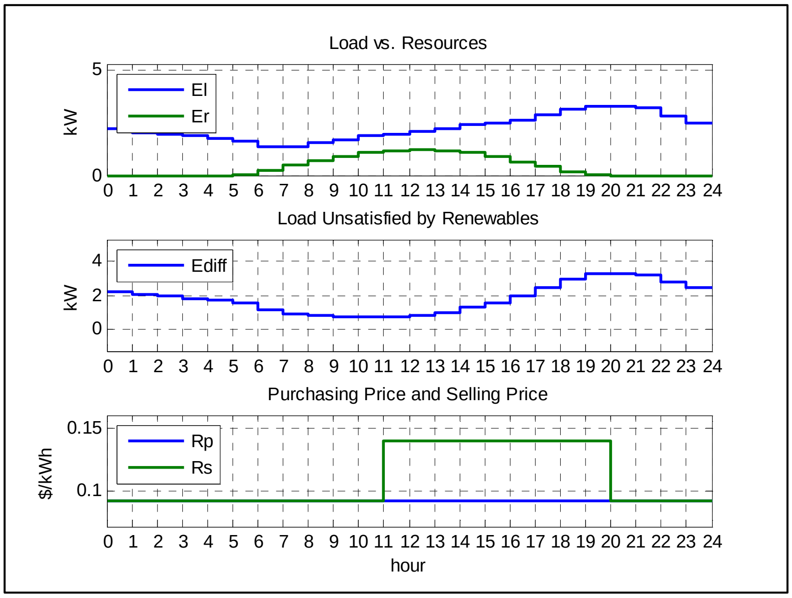

Figure 5.52: Load, Resources, and Rate; July Average

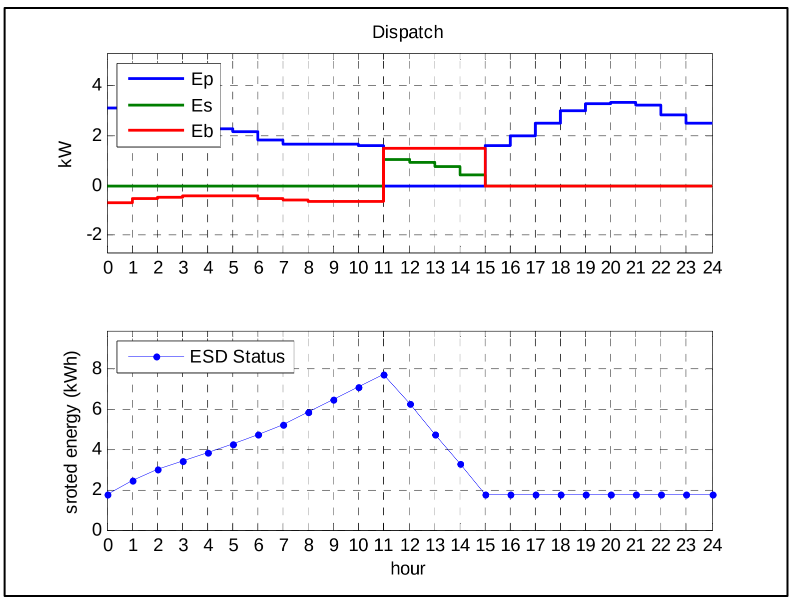

Figure 5.53: Dispatch Schedule for July

Rate 1-5 and 2-5 Hybrid

Under Rate 1-5 Hybrid, $314 is saved annually for a 20 year NPV of negative $13,610. Under Rate 2-5, $318 is saved annually for a 20 year NPV of negative $13,190. The inputs and dispatch for an average July day are shown in Figures 5.54 and 5.55. The Rate 5 dispatch presented here is very similar to the dispatch generated for Rate 4.

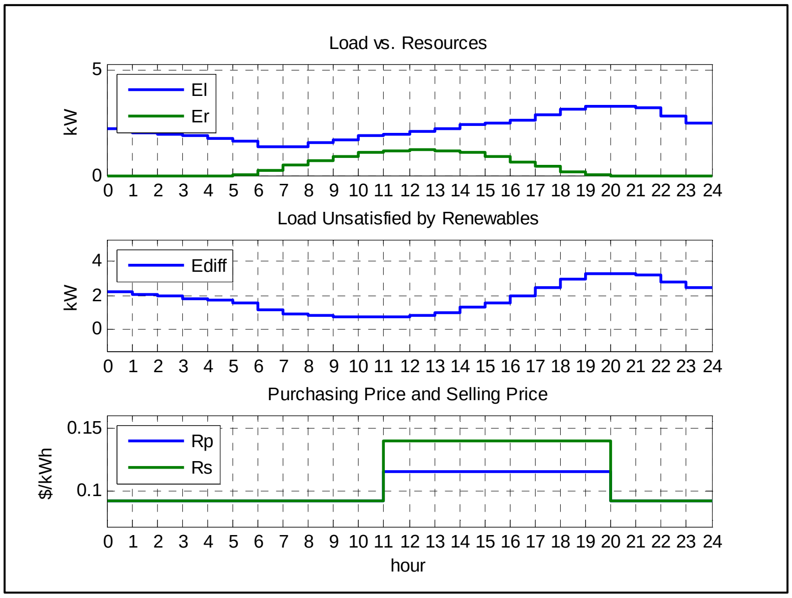

Figure 5.54: Load, Resources, and Rate; July Average

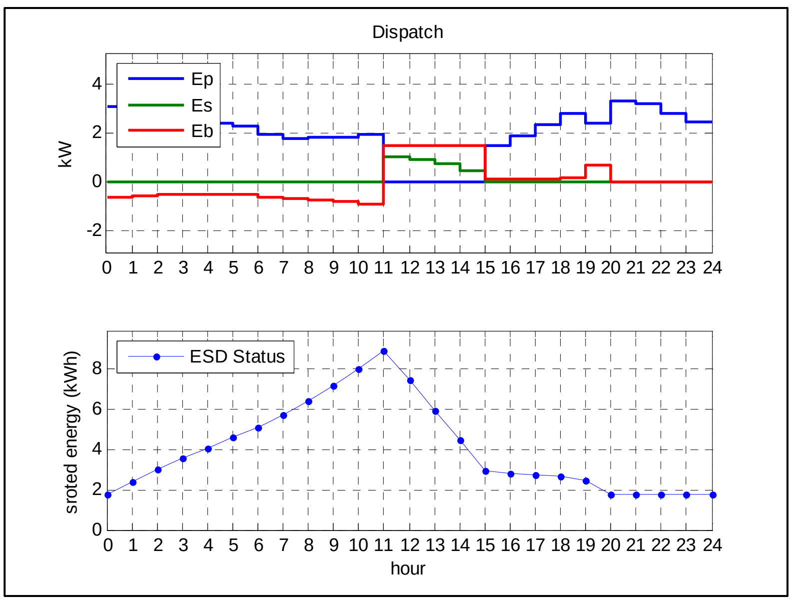

Figure 5.55: Dispatch Schedule for July

Lessons Learned

The solar powered system performs about the same as the wind turbines in the aspect of load cutting/shifting, except that the energy production is not nearly as high. Also, once again, the rate structure found to be most favorable economically is Rate 2-3 Hybrid, but the cost analysis has once again shown that these systems cannot be justified economically with any of these rates or at this location due to the high initial cost of the systems. For the solar based system to break even financially after 20 years, the installation cost would have to decrease dramatically from $16,304 to just $3,300 or the rates would have to increase.

Case Study 4 – Solar System × 2, Load 1, Location 1

In the previous case study, it was found that the solar system was somewhat undersized. Therefore in this case study, the previous solar system is doubled in size and re-examined. While this is most likely not able to make up for the poor NPV numbers, it could help to a certain degree.

System

The only difference from the previous case study is the solar array size, and therefore the cost, of the solar system. The system is now rated at 4.48 kW for a total cost of $29,750. The system constraints are also shown again in Table 5.12 for convenience.

Table 5.12: System Constraints, Case Study 4

Maximum ESD Capacity (kWh)	8.88
Minimum Discharge Level (kWh)	1.77
Maximum Charging per Hour (kWh)	1.32
Maximum Discharging per Hour (kWh)	1.77
Charging Efficiency (%)	76.4
Discharging Efficiency (%)	83.9
Cycling Cost ($/cycle)	0.01

Results

Rate 1

It can be seen in Figures 5.56 and 5.57 that some excess generation is produced with the larger solar array. Some of the excess is used to charge the battery for cutting load later in the day and the rest is sold back to the grid. Under this rate the annual cost savings is found to be $552 for a 20 year NPV of negative $25,663. So while this system has a lower 20 year NPV than the previous solar system, it actually makes back a larger percentage of the initial cost.

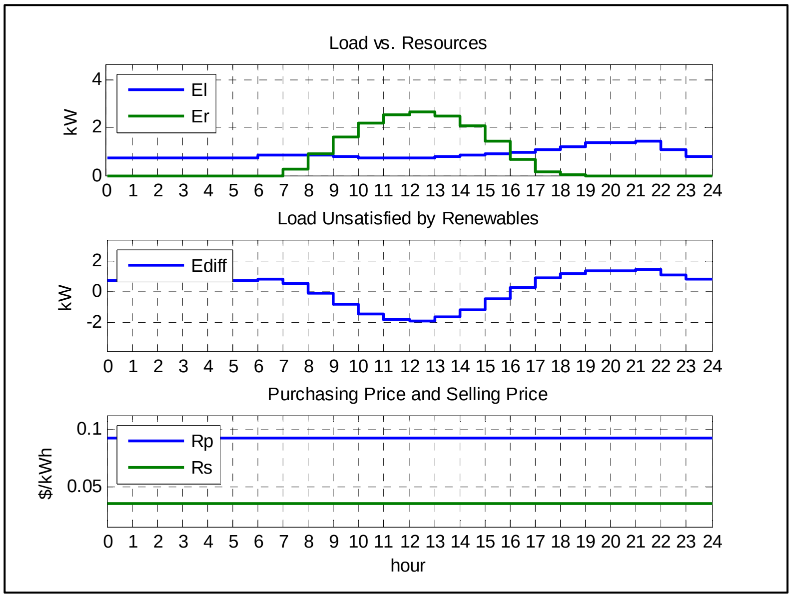

Figure 5.56: Load, Resources, and Rates; February Average

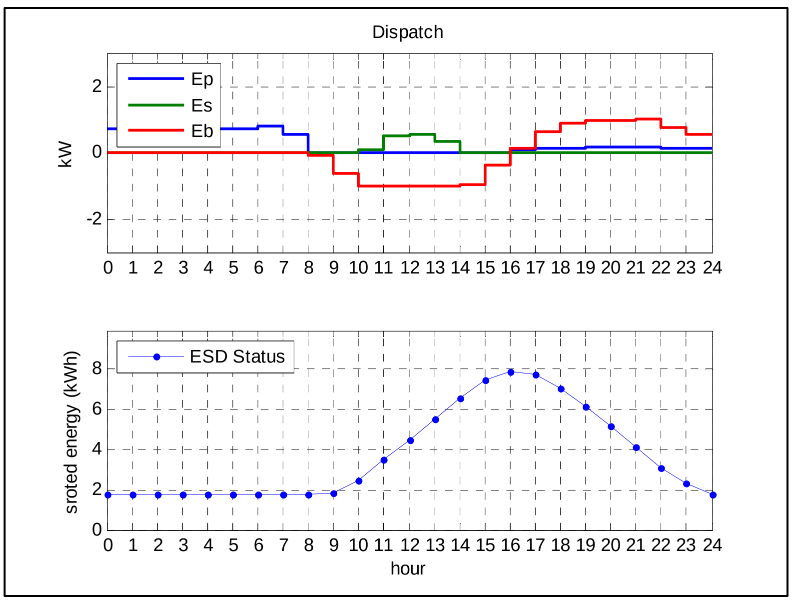

Figure 5.57: February Dispatch

Rate 2

The annual cost saving for the system operating under Rate 2 is found to be $547 for a 20 year NPV of negative $23,967.

Rate 1-3 and 2-3 Hybrid

As in the previous case studies, the system is able to better cut load with Rate 3 in effect. Unlike the smaller solar system, this system is able to utilize excess energy production to help cut the load. Under Rate 1-3, annual cost savings of $613 were attained for a 20 year NPV of negative $24,118. Under Rate 2-3, the annual cost savings were $649 for a 20 year NPV value of negative $23,380.

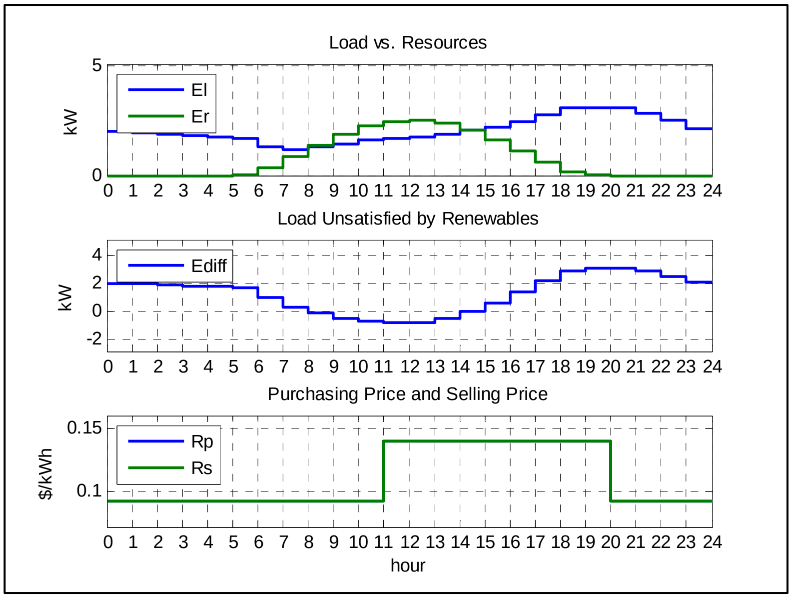

Figure 5.58: Load, Resources, and Rates; August Average

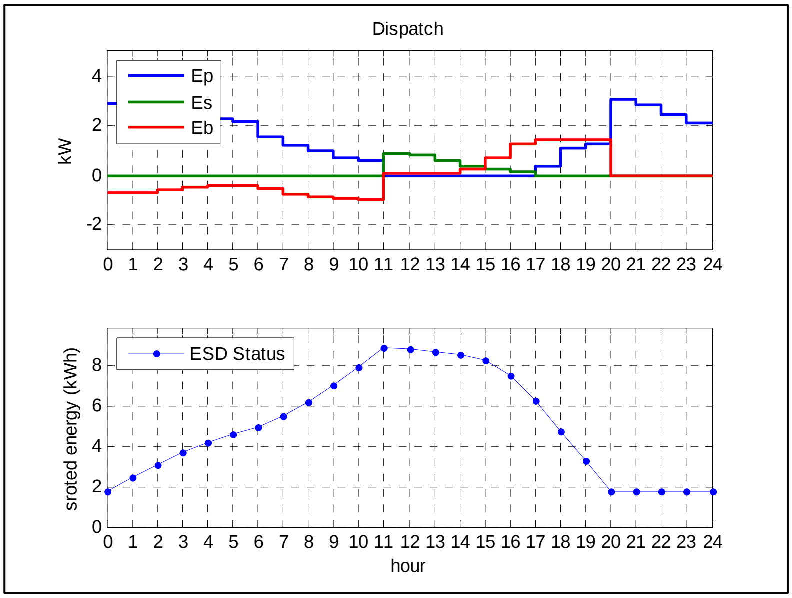

Figure 5.59: August Dispatch

Rate 1-4 and 2-4 Hybrid

With Rate 4 in effect, excess generation and stored load is sold back as quickly as possible once the selling rate goes higher than the purchasing rate, as seen in Figures 5.60 and 5.61. The annual cost savings for Rate 1-4 are $575 for a 20 year NPV of negative $24,843. Under Rate 2-4, annual cost savings of $612 for a 20 year NPV of negative $23,746.

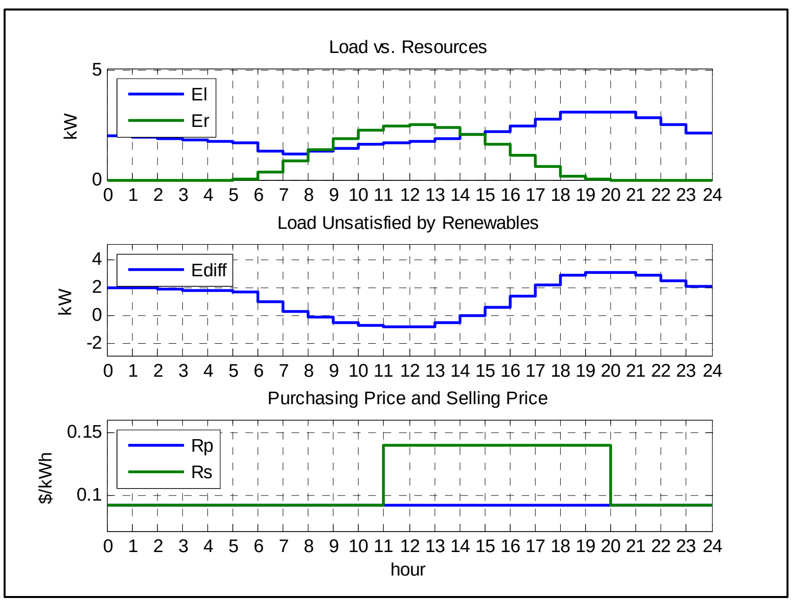

Figure 5.60: Load, Resources, and Rates; August Average

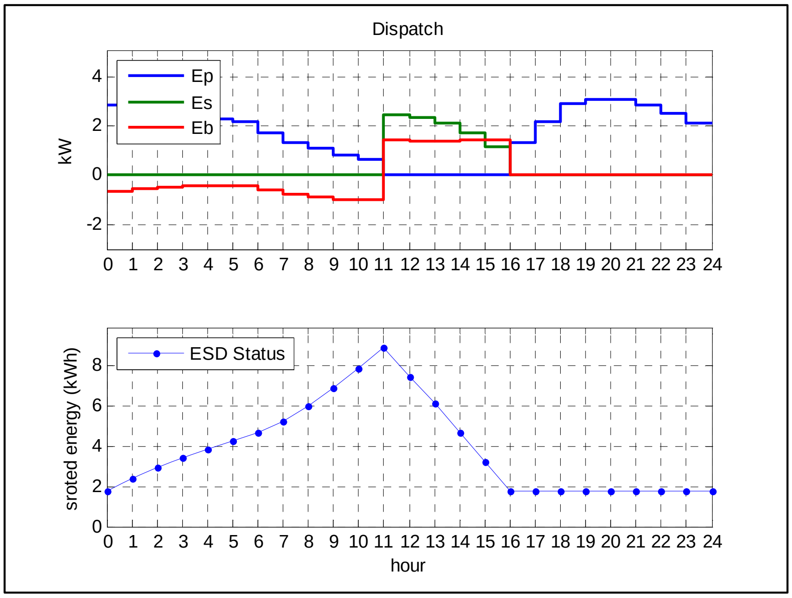

Figure 5.61: August Dispatch Schedule

Rate 1-5 and 2-5 Hybrid

The Rate 5 dispatch, shown in Figures 5.62 and 5.63 is almost identical to the dispatch found for Rate 4. Under Rate 2-5, annual cost savings of $630 for a 20 year NPV of negative $23,563 is found. Under Rate 1-5, annual cost savings of $594 for a 20 year NPV of negative $24,301 is found.

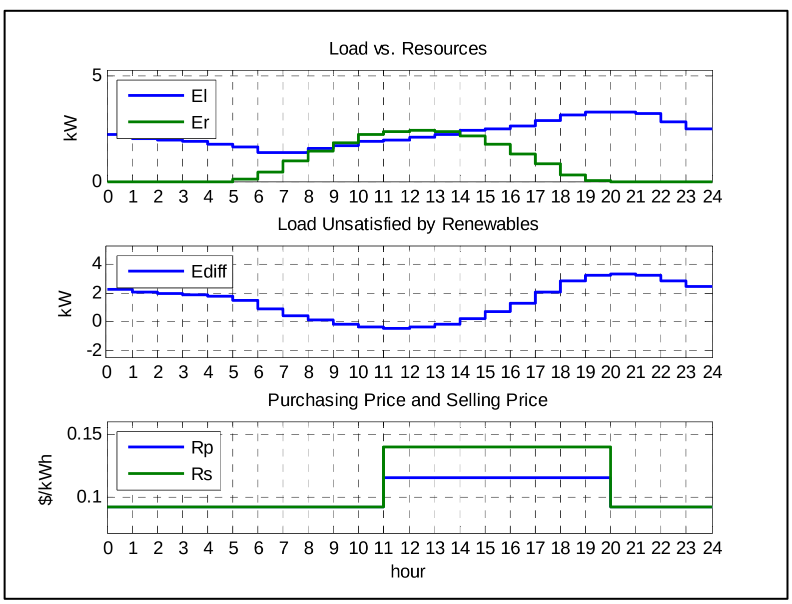

Figure 5.62: Load, Resources, and Rates; July Average

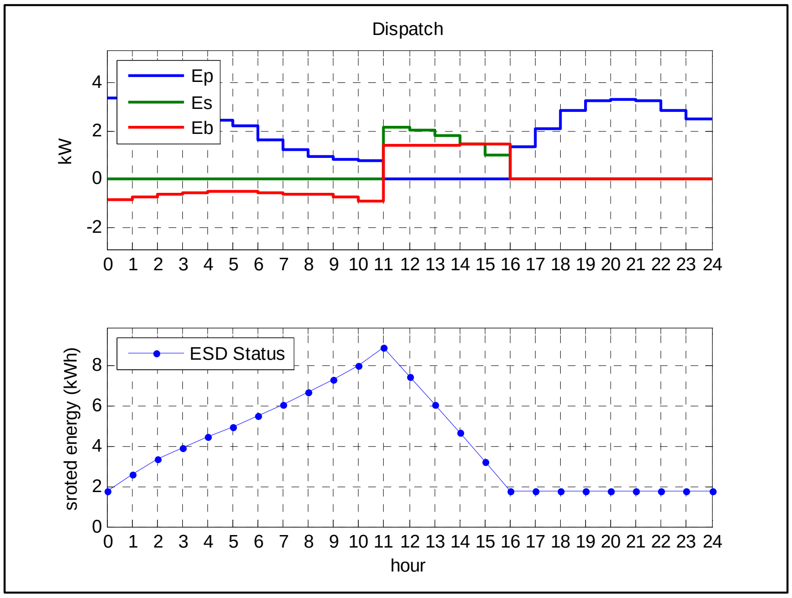

Figure 5.63: July Dispatch Schedule

Lessons Learned

By doubling the size of the solar array, the system is able to more effectively reduce peak load, but the added cost of installing the extra panels and associated hardware leads to an even lower 20 year NPV in all rate cases. However, in terms of comparing to initial cost, doubling the size of the solar array is better economically. With the original system, the best 20 year NPV through all rates is found to be negative $13,306, which is only a 1% gain on the initial investment; but when the panel is doubled in size, the best 20 year NPV is negative $23,380, for a 21% gain on the initial investment.

Case Study 5 – Battery System Only

Case Studies 1 through 4 have shown that a renewable generator combined with a battery storage system cannot be justified economically by the owner of the system given the rates tested. However, a large majority of the cost comes not from the initial cost of the battery system or even replacement of the batteries, but from the renewable generator itself. Therefore a storage system by itself, with no help from a renewable generator, is tested. Results may show that peak shaving alone by purchasing all stored energy from the utility is cost effective. In fact, one paper reviewed has already stated that distributed energy storage is more useful than distributed generation [49].

System

This system once again uses the same battery system that was previously simulated. The constraints of this battery system are given again in Table 5.13.

Table 5.13: System Constraints, Case Study 4

Maximum ESD Capacity (kWh)	8.88
Minimum Discharge Level (kWh)	1.77
Maximum Charging per Hour (kWh)	1.32
Maximum Discharging per Hour (kWh)	1.77
Charging Efficiency (%)	76.4
Discharging Efficiency (%)	83.9
Cycling Cost ($/cycle)	0.01

Results

For this case study, only Rates 1, 2-3, and 2-4 have been implemented. As has been shown throughout this chapter, the economic results tend to be closely related, so it is not necessary to shown them all. These three rates give a good idea of how other rates would perform technically and economically.

Rate 1

Under Rate 1, the battery is never used, because there is never any excess generation and because there is never any incentive to buy excess from the grid since the rates never change.

Rate 2-3 Hybrid

The battery is used heavily in July and August when Rate 3 is in place, because the system can purchase excess energy from the grid while it is cheap and store it in the battery to shift load when the rates increase. Figures 5.64 and 5.65 show the dispatch schedule under Rate 3 for the month of July.

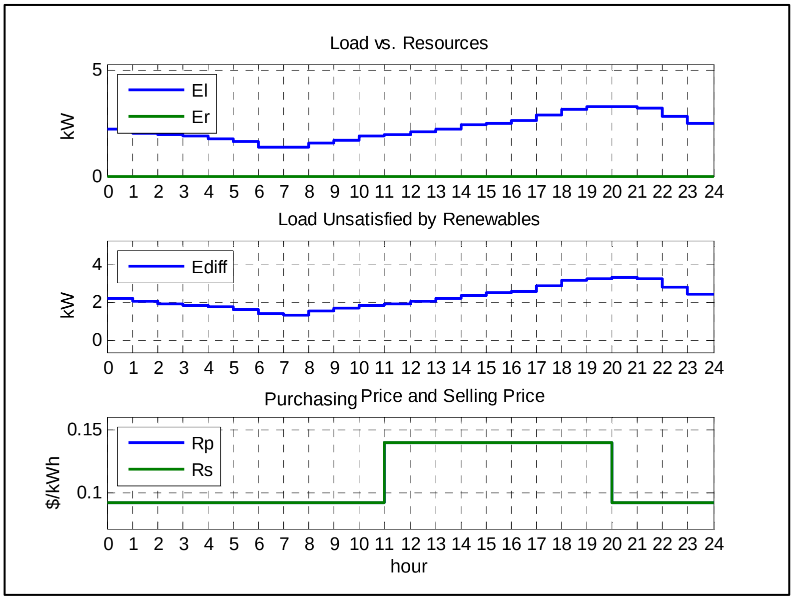

Figure 5.64: Load, Resources, and Rates; July Average

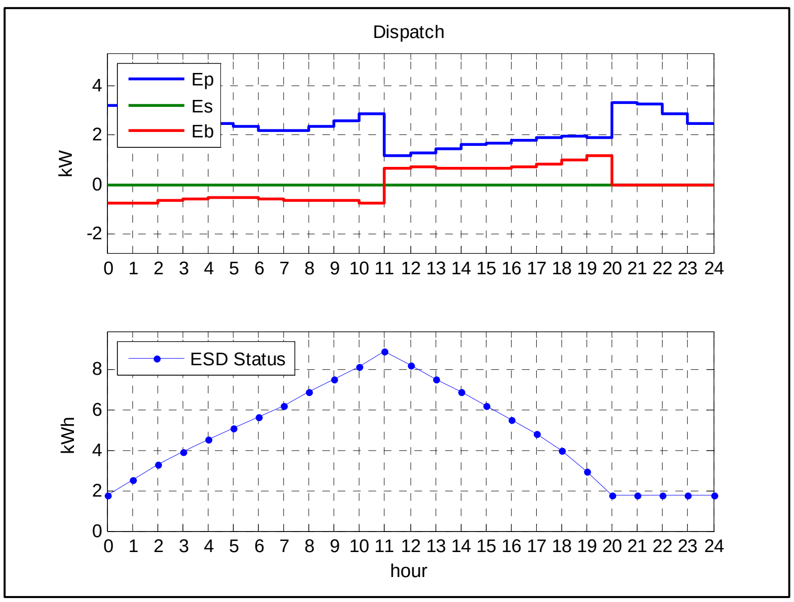

Figure 5.65: Dispatch Schedule for July

Since the battery is only used in two months of the year when Rate 3 is in effect, the annual cost savings are only $20.47, which leads to a 20 year NPV of negative $2,950. This is less money than what is even invested initially, due to the cost of replacement batteries.

Rate 2-4 Hybrid

It is expected that under Rate 4, the battery would charge and discharge similarly to how it did under Rate 3 and similarly to the other case studies. On the contrary it only did so in the non-summer months. During the warmer months, when the load is higher, the battery is never used. This is because the battery can only discharge 1.77 kWh of energy every hour, which in the summer months is never enough to completely cover the load and get to a point where energy is being sold back to the grid. So in this case, the system is never able to take advantage of the time periods when the selling price is higher than the purchasing price. Figures 5.66 and 5.67 show this occurrence in more detail. Even though Rate 4 is not implemented in June, showing how the system reacts to Rate 4 in June is more interesting than in July or August when the battery is never charged or discharged. It can be seen that only in the 12th and 13th hours is the load low enough for the system to be in a position to sell energy back to the grid and utilize the high selling price.

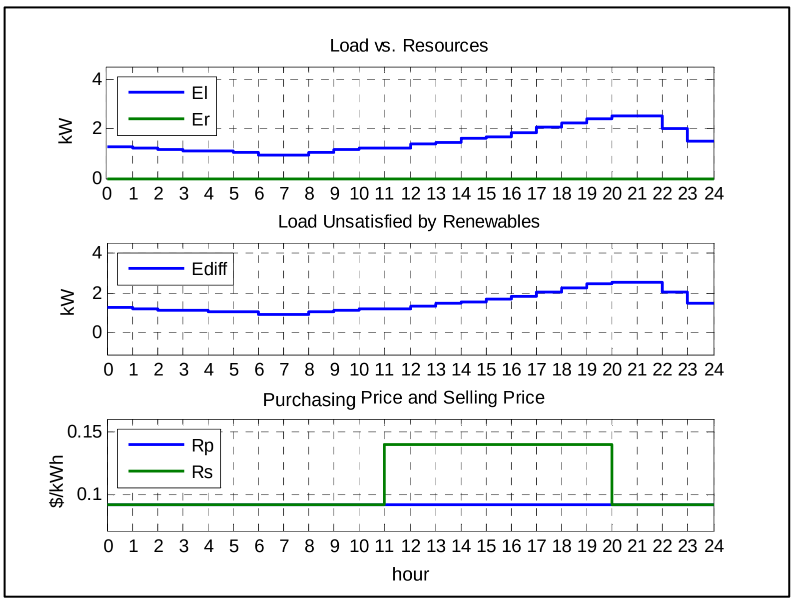

Figure 5.66: Load, Resources, and Rates; June Average

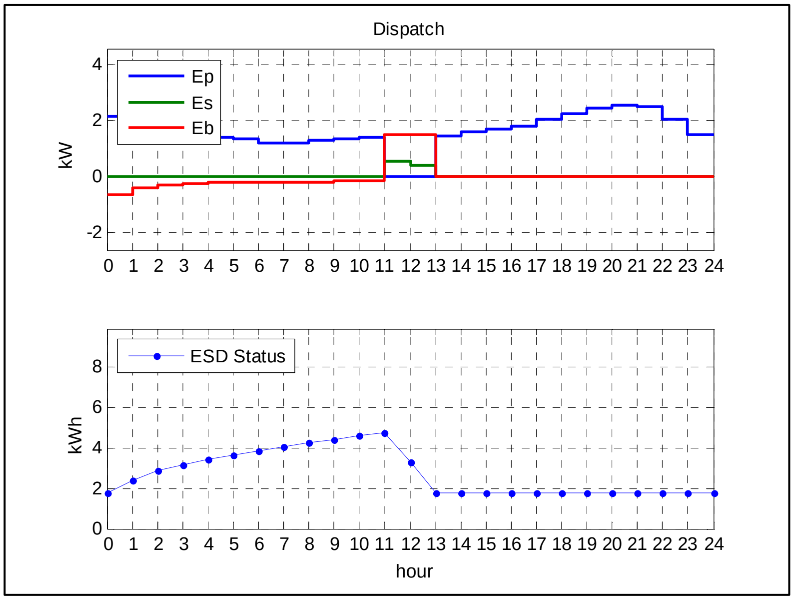

Figure 5.67: Dispatch Schedule for June

Lessons Learned

It was thought that eliminating the renewable generator along with the high cost of installing it could lead to an economically feasible system. However, simulation showed that without the generator, not enough energy could be cheaply shifted to make a large enough annual savings to recoup the cost of just the battery system. The 20 year NPV under each rate case is still negative. The rate case that fared best economically for this case study is a tie between Rate 1 and Rate 2-4 Hybrid, but this is only because these rates did not cause the battery to cycle as much and require replacement. Since the battery did not cycle at all during the peak months when Rate 4 is in effect, the cost under Rate 2-4 is the same as the cost under Rate 1. The battery would need to be sized up to make more of an economic impact, but that would also add to initial cost. For this system to break even at 20 years under Rate 2-3, the cost of the batteries would have to be reduced from $1,040 to $200 and the cost of the inverter would have to be reduced from $1,830 to $250. However, cheaper, higher capacity ESDs, such as the EESU mentioned in Chapter 2, may be available in the near future.

It is not necessary to test other rate structures on this system. Rate 2-3 Hybrid has consistently done the best economically. Therefore, if the system cannot be cost justified under Rate 2-3 Hybrid, it is not cost justifiable under any other rate.

Case Study 6 – Increased Rates with Best Wind Powered Option

Case Studies 1 though 5 have shown that a battery system, with or without a renewable generator, can effectively shift load. This could be very beneficial to a capacity constrained utility, but so far none of the systems have been economically feasible for the owner of the system. It may be that the only way these system can be cost justified is if the cost of energy were to be higher. Previous research has already shown that these systems may not be cost justifiable in Kansas where the cost of energy is low, but may easily be cost justifiable in other areas such as Hawaii where current average cost of electricity is three times that of the Kansas average [1].

System

In the previous simulations, the system that made up the most ground on recovering the initial investment is the Skystream 3.7-based system, examined in Case Study 1. Therefore, it is used again for this simulation along with the same battery system that has been used in all previous studies.

This time, the simulation occurs in Dodge City since the wind conditions are more favorable there. This system is connected to Load 3 since it uses the most energy and therefore has the most potential for cost savings.

Results

Rate 2-3 Hybrid × 2

Even though Rate 2 has been doubled here, the cost of energy still does not change throughout the day on an hourly basis, so for the non-peak months the battery is not cycled just as in the other case studies for Rate 2. Rate 3 however, is once again successful at reducing peak load as seen in Figures 5.68 and 5.69. At this residence though, the peak rates did not match this load as well as they matched Load 1, so the highest demand time for this load is not reduced. In the real world though, it would be up to the utility to define the peak demand time.

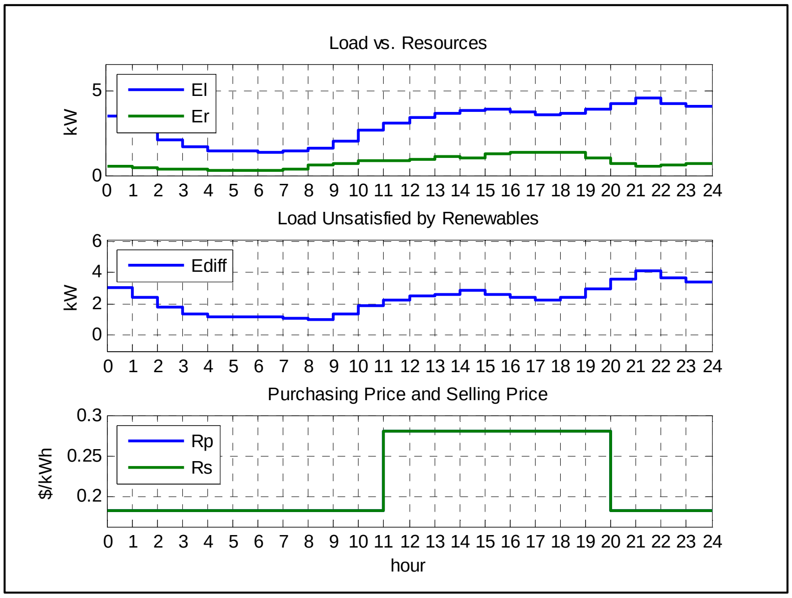

Figure 5.68: Load, Resources, and Rates; July Average

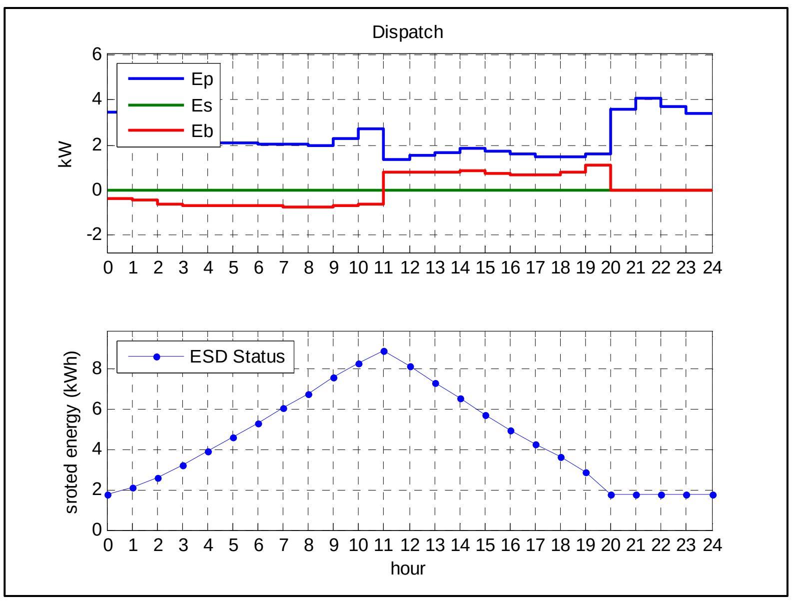

Figure 5.69: Dispatch Schedule for July

The system simulated under this rate structure performed very well economically, saving $1,493 annually, but more importantly had a 20 year NPV of positive $1,293 when compared to satisfying this load without the Skystream and a dispatchable battery system. This of course can be attributed mostly to doubling the cost of energy, but also to siting the system in an area with better wind and at a residence with higher load.

Rate 2-3 Hybrid × 3

This rate structure actually produced the same exact dispatch as the Rate 2-3 Hybrid × 2. The only difference is the cost of energy is higher leading to an expected better rate of return.

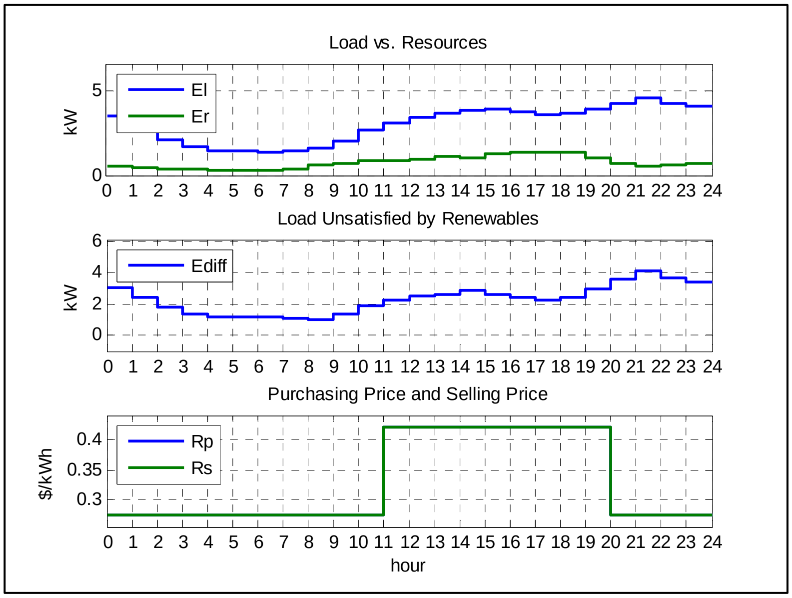

Figure 5.70: Load, Resources, and Rates; July Average

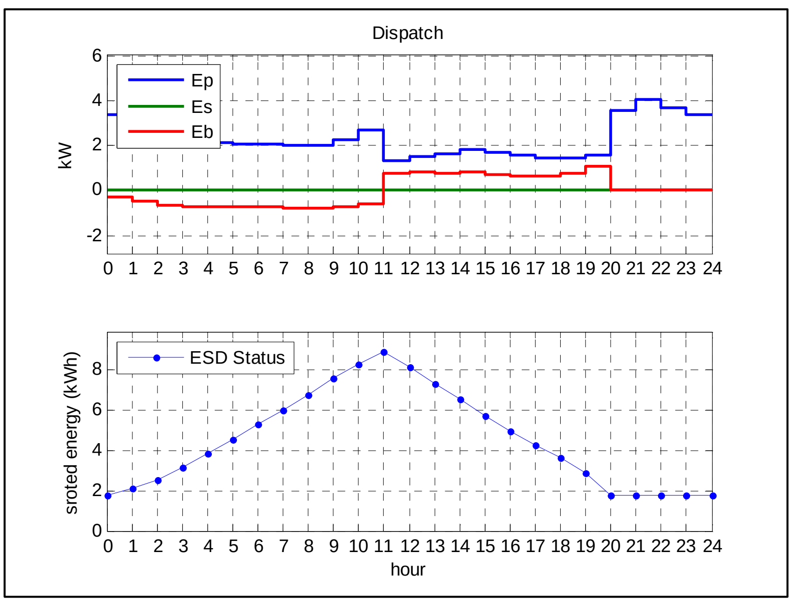

Figure 5.71: Dispatch Schedule for July

While the dispatch is the same, the annual energy savings were much higher as expected at $2,240 with an incredible 20 year NPV of $8,625 when compared to having no system at all.

Lessons Learned

The average cost of energy in Kansas is known to be comparatively low at only 8.07 cents/kWh [50]. 39 states currently have higher average rates, with 8 states having rates higher than 16 cents/kWh and Hawaii having the highest rates at an average of 29.28 cent/kWh [50]. So doubling or even tripling the energy rates for these simulations is not unrealistic. Additionally, many of these states offer financial incentives not available in Kansas which would allow the owner to break even on the initial investment even faster.

It was also learned through the simulations done in Case Study 6 that the dispatch does not change if the energy rates are simply scaled up and down. Rather, the dispatch compares the rate against itself on an hour-by-hour basis.

Case Study 7 – Increased Rates with Best Solar Powered Option

The previous case study, Case Study 7, has shown that with increased rates, these systems can become economically feasible. However, that case study is done on the best performing system, which is the Skystream 3.7 wind turbine. It is also useful to determine if a solar system with dispatchable energy storage becomes feasible by doubling and tripling the cost of energy. Both solar systems previously tested performed very poorly from an economic standpoint, however, the 2.24 kW system did slightly better as it recouped a few percent more of the initial cost.

System

The system to be studied is a 2.24 kW solar array made up of SGT 160 solar panels. As in all the previous case studies, Trojan T105 batteries are used to form an 8.88 kWh battery bank. Also, this system is connected to Residence 1 in Manhattan, KS.

Table 5.14: System Constraints, Case Study 7

Maximum ESD Capacity (kWh)	8.88
Minimum Discharge Level (kWh)	1.77
Maximum Charging per Hour (kWh)	1.32
Maximum Discharging per Hour (kWh)	1.77
Charging Efficiency (%)	76.4
Discharging Efficiency (%)	83.9
Cycling Cost ($/cycle)	0.01

Results

Rate 2-3 Hybrid × 2

With the peak demand identified by the increase in rates of Rate 3, the dispatch algorithm is once again able to cut peak. Some of the peak is reduced by the solar system, but that is done in a passive manner as there is never any excess production. However, some energy is purchased in the morning during the low cost of energy time and actively dispatched by the system so that it is used during the high cost of energy time. Figure 5.72 and 5.73 show the dispatch for July under Rate 3 × 2.

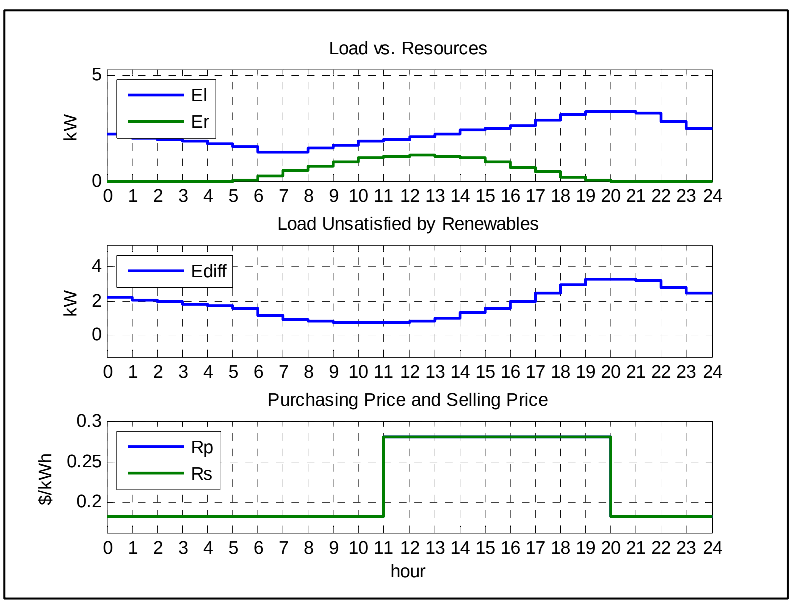

Figure 5.72: Load, Resources, and Rates; July Average

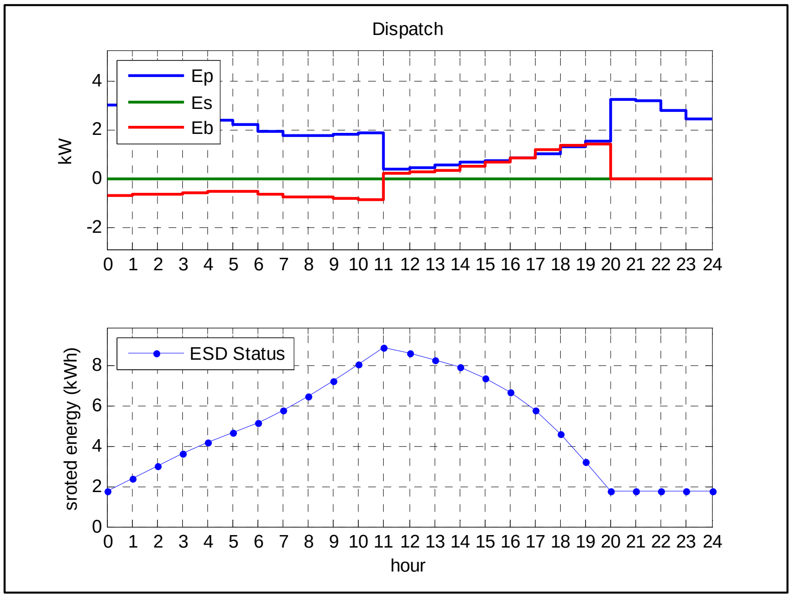

Figure 5.73: Dispatch Schedule for July

Unfortunately, even with the rates doubled, the system is still economically unfeasible. The 20 year NPV of the system came to be negative $9,739.

Rate 2-3 Hybrid × 3

With the rates tripled, the dispatching algorithm produced a nearly identical dispatch to when the rates were only doubled. This can be seen in Figures 5.74 and 5.75.

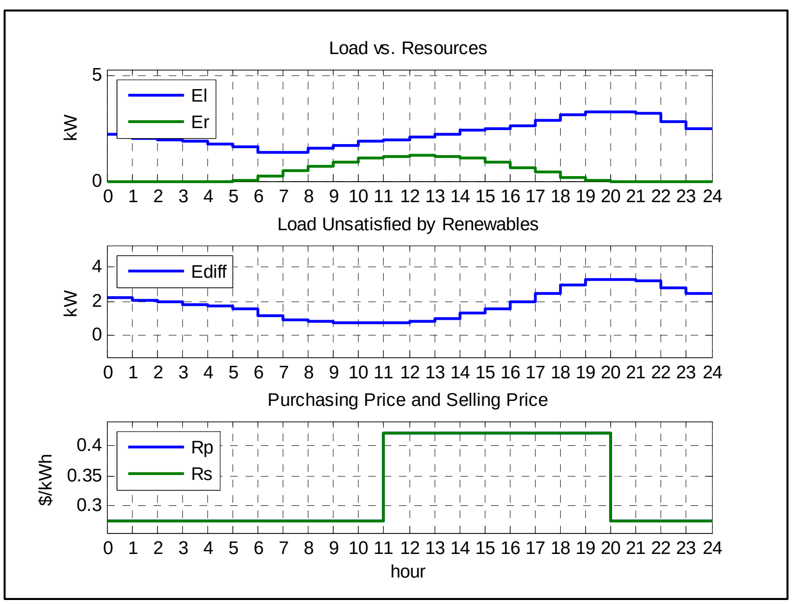

Figure 5.74: Load, Resources, and Rate; July Average

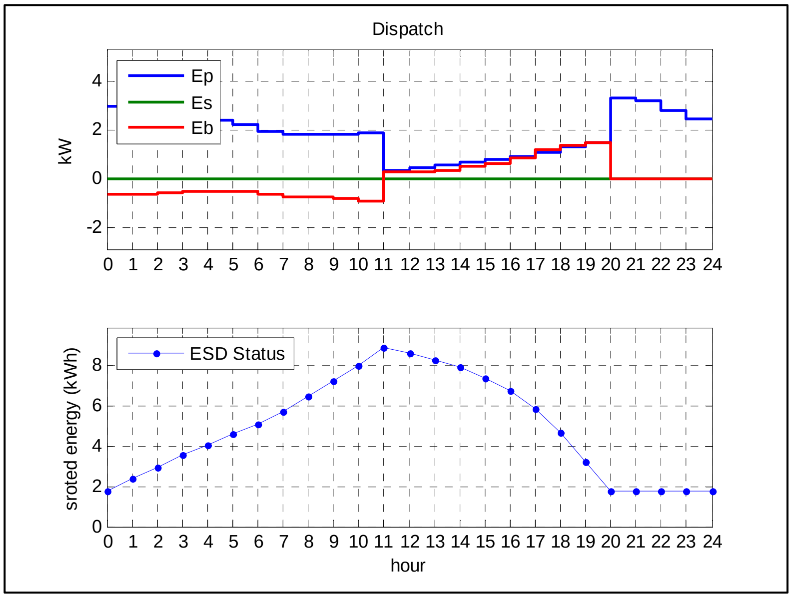

Figure 5.75: Dispatch Schedule for July

Even with the rates tripled here, the system does not justify the initial cost. The 20 year NPV of the system comes to be negative $6,453.

Lessons Learned

Through this case study, it has been shown that even when the rates are doubled and tripled, the system with a solar generator cannot be economically justified. It could also be argued that it did not perform as well as some of the other systems from a technical standpoint because the system never generated excess energy that could be shifted to the peak demand time, which stems from the fact that there is just not much solar energy available at this location. In fact, the maximum hourly average flat plate solar irradiance at this location is only 0.63 kW/m^2, so the solar array never produces at its rated power output (which would occur at 1 kW/m^2). Therefore, it is useful to see how the system performs in areas with better solar isonolation such as the Southwest.

Case Study 8 – Increased Rates with Best Solar Option in Southwest

It is shown in the previous two case studies that increasing the rates by a factor of two and three can make some renewable generators, such as the Skystream 3.7, coupled with dispatchable ESD economically feasible. However, a solar powered generator that is economically justifiable still has not been found. Relocating the system to an area with better solar isonolation, in addition to the higher rates, might change this. As shown previously, the annual average number of peak sun hours falling on a flat plate collector in Manhattan is only 3.49. Furthermore, by viewing the map in Figure 5.6 it can be see that the average annual number of peak sun hours in Kansas is in the 4 to 5 range and in the Southwest it is in the 5 to 6 range. So the previous solar case studies somewhat underrepresented Kansas, but even more benefit can be gained by modifying the data to represent good location in the Southwest. At the high end solar areas of the Southwest region, 71% more sunshine falls on a flat plate collector than in location at which the original solar data set was taken. Therefore, the solar data is multiplied by 1.71 prior to simulation.

System

This system is the same as that of Case Study 7, a 2.24 kW solar array with an 8.88 kWh battery system. The constraints for the battery system are shown again in Table 5.15.

Table 5.15: System Constraints, Case Study 7

Maximum ESD Capacity (kWh)	8.88
Minimum Discharge Level (kWh)	1.77
Maximum Charging per Hour (kWh)	1.32
Maximum Discharging per Hour (kWh)	1.77
Charging Efficiency (%)	76.4
Discharging Efficiency (%)	83.9
Cycling Cost ($/cycle)	0.01

Results

Rate 2-3 Hybrid × 2

It can be seen in Figures 5.76 and 5.77 that changing locations greatly increased the amount of solar resources that could be gathered by the solar system. This in turn led to a very different dispatch from the previous case study. In this dispatch, much more energy is sold back to the grid and the use of the battery to cut load is delayed until later in the day. Throughout much of the peak period the load is completely eliminated.

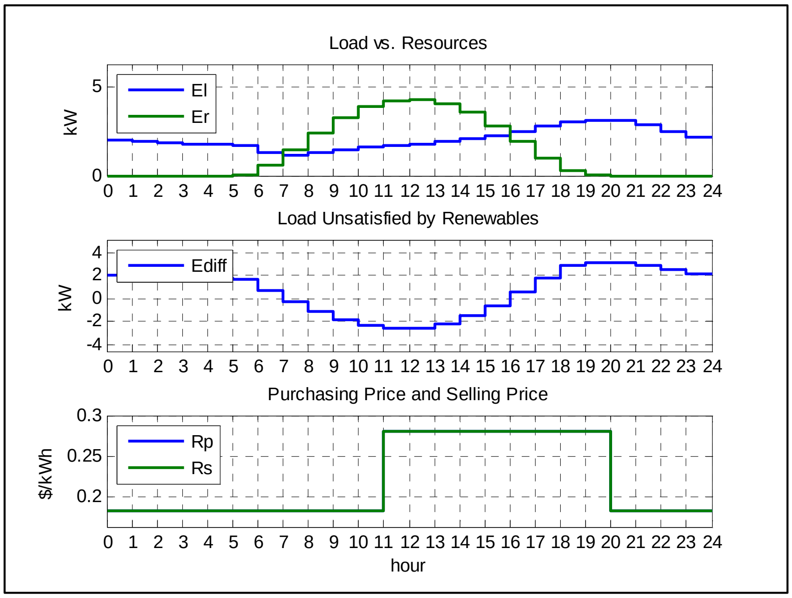

Figure 5.76: Load, Resources, and Rates; August Average

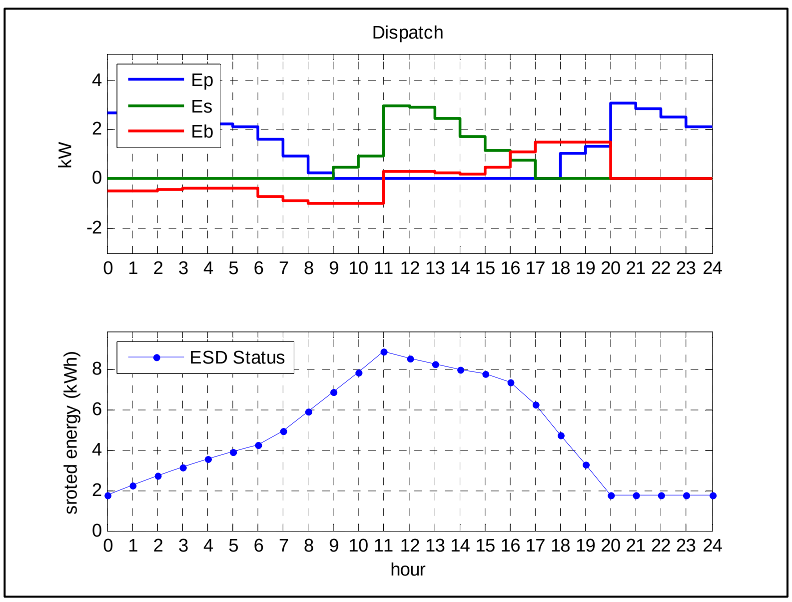

Figure 5.77: Dispatch Schedule for August

With the increase in solar availability, the economic feasibility greatly increased. In this location, the system is now economically feasible with a 20 year NPV of positive $5,190. This is the first case study in which a solar system has been found to be economically justifiable. Also, this system works out better economically than the Skystream 3.7 with doubled electric rates.

Rate 2-3 Hybrid × 3

With the rates tripled, rather than doubled, the system produced the same dispatch, as can be seen in Figures 5.78 and 5.79.

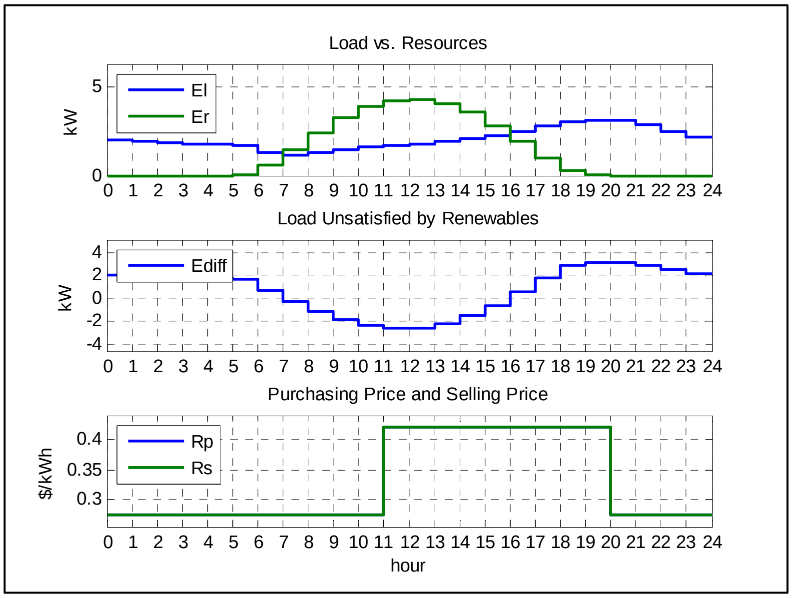

Figure 5.78: Load, Resources, and Rates; August Average

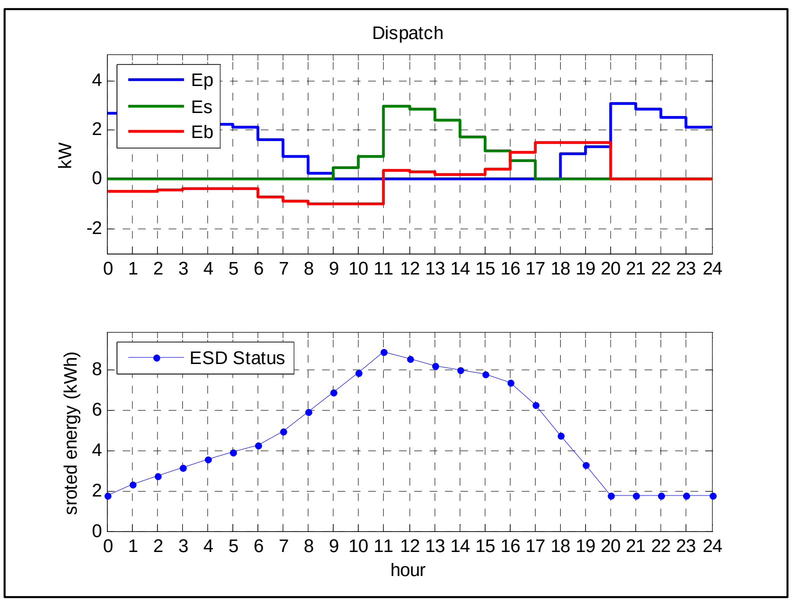

Figure 5.79: Dispatch Schedule for August

Tripling the rates of course leads to an even better 20 year NPV of positive $15,940. Of all the simulation performed, this has been the best from an economic standpoint.

Lessons Learned

Although doubling and even tripling the electric rates for the solar system located in Manhattan could not make it economically feasible, moving the system to better solar location made it very economically justifiable.

Chapter Summary

A great deal of information has been presented in the seven case studies given in this chapter and a summary of the general trends as well as the most useful lessons learned needs further attention.

Technical Performance

It was found that systems operating under Rate 1 would utilize the battery effectively, but only when excess energy is produced. This is because it is much better to use the excess energy to cut load later in the day than to sell it back to the grid at a lower price. However, this is in contrast to the performance of the system under some other rates when the battery would be used regardless of the presence of excess energy production. However, this makes sense because under Rate 1 there is never any incentive to buy excess energy when the rates remain the same all day long. If excess were purchased from the grid, it would be at a net loss on the day as it would be used to cut load purchased at the same price and some of the energy would be lost in charging and discharging the battery system.

It was found that under Rate 2, the static net metering rate, an ESD is completely unnecessary as it is never used. This also makes sense because with Rate 2 in place the grid can be used as a form of ESD with no losses from the customer's point of view. So rather than store energy in a battery system for use later in the day, with some of the energy being lost in the charging and discharging process, the excess can simply be sold back to the grid immediately and more can be purchased later in the day at the same price.

Under all the other rate cases, the cost of energy changed depending on how and when the energy is used. Under these cases, the dispatching algorithm is very effective at storing not only excess energy produced by the renewable generators, but also excess purchased from the grid to find the most economic dispatching schedule. Under these rate cases the battery is cycled almost daily, however, there were some exceptions under Rate 4. Under Rate 4 the purchasing price of energy remained the same all day while the selling price increased to greater than the purchasing price during the peak hours. The reason the battery is sometimes not cycled or only partially cycled is because, limited by the maximum discharging constraint, the system could sometimes never cut enough load to get to a point where energy is being sold back to the grid.

With peak demand times identified by the electric provider through the electric rates, the dispatching algorithm is very successful at cutting/shifting peak load. With higher capacity ESD systems the potential for load leveling is even higher with more potential for purchasing excess in the off-peak hours or better utilizing excess energy production by renewable generators.

Economic Performance

Most of the systems simulated through these case studies were found to be economically unjustifiable including all of those based on current electric prices typical of Kansas. However, with electric rates increased by a factor of two and with the systems sited in better locations depending of the type of renewable generator, both the wind and solar based systems became economically feasible. Results of the 20 year NPV for all the systems and rates studied are presented in Tables 5.16 to 5.23 at the end of this section. These tables show not only the 20 year NPV of installing a renewable generator and dispatchable battery system, but also the NPV of installing just a renewable generator and the NPV of adding a dispatchable battery system to a previously installed renewable generator.

It can be seen that in all case studies, with the exception of Case Study 5, that Rate 2-3 Hybrid performed the best economically. This should be the case as the sum of the cost of energy throughout the day under Rate 2-3 Hybrid is higher than any other rate structure allowing for higher potential savings in cutting load and increasing the worth of the excess energy whether it is used for load cutting or selling back to the grid. Although, it should be pointed out that while Rate 2-3 Hybrid has the most potential for savings by installing a renewable generator and/or battery system, it is also the most expensive rate structure to operate a load on. Just like the case studies when the rates were doubled and tripled, the high cost of energy allowed for the greatest potential savings.

The reason Rate 2-3 Hybrid is the worst economically under Case Study 5, shown in Table 5.20, is because of the replacement cost of batteries. In both Rate 2 and Rate 2-4 Hybrid the battery is never used.

While it is shown that both a renewable generator with a dispatchable ESD and a renewable generator by itself is economically justifiable given a high enough cost of energy and proper siting, simply adding a dispatchable battery system to an existing renewable generator is never found to be economically justifiable. Furthermore, a battery system by itself, while it performed well from a technical standpoint, performed terribly from an economic standpoint with the 20 year NPV found to be lower than the initial installation cost due to the replacement costs of batteries. This is shown in Table 5.20. At the current cost per kWh for batteries, it is simply not feasible to install dispatchable ESD systems. However, as it has been shown in Chapter 3, technological improvements to ESDs may lead to cheaper, higher capacity energy storage systems in the near future. Should this happen, adding a dispatchable ESD to an existing generator is likely to become economically justifiable. When that time comes, the dispatching algorithm developed here could be used along with the ESD to improve the rate of return seen by the owners of these systems.

Table 5.16: Case Study 1, NPV Results vs. Electric Rate

Case Study 1 – Skystream 3.7, Load 1, Location 1			
Rate	**20 Year NPV ($)**		
	DRE vs. none	**R vs. none**	**DRE vs. R**
1	-8,630	-5,806	-3,208
2	-7,685	-4,815	-2,870
1-3 Hybrid	-8,223	-4,845	-2,698
2-3 Hybrid	-7,219	-4,550	-2,950
1-4 Hybrid	-8,634	-5,110	-2,844
2-4 Hybrid	-7,630	-4,815	-3,095
1-5 Hybrid	-8,428	-4,977	-2,771
2-5 Hybrid	-7,424	-4,682	-3,023

DRE vs. none: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load without either

R vs. none: cost of satisfying the load with a renewable generator versus the cost of satisfying the load without a generator, in either case there is no ESD and therefore no dispatching algorithm

DRE vs. R: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load with only a renewable generator

Table 5.17: Case Study 2, NPV Results vs. Electric Rate

Case Study 2 – Bergey Excel-S, Load 1, Location 1			
Rate	**20 Year NPV ($)**		
	DRE vs. none	**R vs. none**	**DRE vs. R**
1	-32,790	-30,175	-2,615
2	-28,215	-25,345	-2,870
1-3 Hybrid	-31,515	-29,416	-2,099
2-3 Hybrid	-27,369	-24,700	-2,669
1-4 Hybrid	-32,064	-29,965	-2,099
2-4 Hybrid	-27,918	-25,250	-2,669
1-5 Hybrid	-31,789	-29,690	-2,099
2-5 Hybrid	-27,644	-24,975	-2,669

DRE vs. none: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load without either

R vs. none: cost of satisfying the load with a renewable generator versus the cost of satisfying the load without a generator, in either case there is no ESD and therefore no dispatching algorithm

DRE vs. R: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load with only a renewable generator

Table 5.18: Case Study 3, NPV Results vs. Electric Rate

Case Study 3 – 2.24 kW Solar Array, Load 1, Location 1			
Rate	**20 Year NPV ($)**		
	DRE vs. none	**R vs. none**	**DRE vs. R**
1	-13,456	-10,803	-2,653
2	-13,419	-10,549	-2,870
1-3 Hybrid	-13,444	-10,609	-3,493
2-3 Hybrid	-13,024	-10,356	-2,669
1-4 Hybrid	-13,768	-10,803	-3,623
2-4 Hybrid	-13,348	-10,549	-2,799
1-5 Hybrid	-13,610	-10,706	-3,561
2-5 Hybrid	-13,190	-10,452	-2,738

DRE vs. none: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load without either

R vs. none: cost of satisfying the load with a renewable generator versus the cost of satisfying the load without a generator, in either case there is no ESD and therefore no dispatching algorithm

DRE vs. R: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load with only a renewable generator

Table 5.19: Case Study 4, NPV Results vs. Electric Rate

Case Study 4 – 4.48 kW Solar Array, Load 1, Location 1			
Rate	**20 Year NPV ($)**		
	DRE vs. none	**R vs. none**	**DRE vs. R**
1	-25,663	-22,589	-3,074
2	-23,967	-21,097	-2,870
1-3 Hybrid	-24,118	-22,124	-1,994
2-3 Hybrid	-23,380	-20,711	-2,669
1-4 Hybrid	-24,484	-22,467	-2,017
2-4 Hybrid	-23,746	-21,054	-2,692
1-5 Hybrid	-23,301	-22,296	-2,005
2-5 Hybrid	-24,350	-20,883	-2,680

DRE vs. none: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load without either

R vs. none: cost of satisfying the load with a renewable generator versus the cost of satisfying the load without a generator, in either case there is no ESD and therefore no dispatching algorithm

DRE vs. R: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load with only a renewable generator

Table 5.20: Case Study 5, NPV Results vs. Electric Rate

Case Study 5 – Stand Alone Battery System, Load 1	
Rate	**20 Year NPV ($)**
	DE vs. none
2	-2870
2-3 Hybrid	-2950
2-4 Hybrid	-2870

DE vs. none: cost of satisfying the load with a dispatchable ESD versus the cost of satisfying the load without it, in either case there is no renewable generator

Table 5.21: Case Study 6, NPV Results vs. Electric Rate

Case Study 6 – Skystream 3.7, Load 3, Location 2			
Rate	**20 Year NPV ($)**		
	DRE vs. none	**R vs. none**	**DRE vs. R**
2-3 Hybrid × 2	1,293	3,761	-5470
2-3 Hybrid × 3	8,625	10,892	-2548

DRE vs. none: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load without either

R vs. none: cost of satisfying the load with a renewable generator versus the cost of satisfying the load without a generator, in either case there is no ESD and therefore no dispatching algorithm

DRE vs. R: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load with only a renewable generator

Table 5.22: Case Study 7, NPV Results vs. Electric Rate

Case Study 7 – 2.24 kW Solar Array, Load 1, Location 1			
Rate	**20 Year NPV ($)**		
	DRE vs. none	**R vs. none**	**DRE vs. R**
2-3 Hybrid × 2	-9,739	-7,271	-2,468
2-3 Hybrid × 3	-6,453	-4,186	-2,267

DRE vs. none: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load without either

R vs. none: cost of satisfying the load with a renewable generator versus the cost of satisfying the load without a generator, in either case there is no ESD and therefore no dispatching algorithm

DRE vs. R: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load with only a renewable generator

Table 5.23: Case Study 8, NPV Results vs. Electric Rate

Case Study 8 – 2.24 kW Solar Array, Load 1, Located in Southwest USA			
Rate	**20 Year NPV ($)**		
	DRE vs. none	**R vs. none**	**DRE vs. R**
2-3 Hybrid × 2	5,190.05	7,658.00	-2,467.95
2-3 Hybrid × 3	15,940.07	18,206.99	-2,266.92

DRE vs. none: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load without either

R vs. none: cost of satisfying the load with a renewable generator versus the cost of satisfying the load without a generator, in either case there is no ESD and therefore no dispatching algorithm

DRE vs. R: cost of satisfying the load with a renewable generator and dispatchable ESD versus the cost of satisfying the load with only a renewable generator

CHAPTER 6 - Conclusions

Through this research, an algorithm for creating dispatching schedules for customer-owned renewable energy systems coupled with energy storage has been developed, otherwise known as the IDDRR Algorithm. The IDDRR algorithm is based on linear programming. It is envisioned that adding dispatchable energy storage along with this algorithm to renewable generators would increase the rate of return for the owner of the system and help the utility shave peak load. To insure the algorithm works properly, it has been tested on several realistic systems which has shown that it can effectively reduce peak demand, especially when peak demand times are identified by increased rates. However, the costs of the systems studied heavily outweighed the economic benefits at the current rates seen in the state of Kansas. On the other hand, simulating the dispatching algorithm with increased rates that are similar to the levels experienced by many other states has shown that renewable generators can easily be cost justified in the right areas, but the ESD system is still too expensive at today's prices. However, technical improvements and cost reduction in ESD systems may soon provide economically feasible storage systems. Should that happen, it is recommended that the IDDRR Algorithm, or some other dispatching algorithm, be implemented in real systems.

Of the systems simulated in the state of Kansas, the battery coupled with the Skystream 3.7 wind turbine seemed to fare the best in relation to the cost of installation. The fourth system studied, just a battery without any renewable generator, is also able to shift peak using only energy purchased from the grid early in the day, but due to the high cost of batteries is the most uneconomical when compared to initial cost of installation. Overall, the system that performed the best economically is the solar system located in the Southwest, due to the high levels of solar irradiance in that area.

Future Work

While the IDDRR Algorithm is capable of optimizing energy flows to the highest degree possible under the constraints of linear programming, many of the components of a battery-based system are not linear in reality. For a more accurate dispatching algorithm, quadratic programming should be used. However, quadratic programming can be computationally intensive. Rewriting the IDDRR Algorithm as an Integer Program or Mixed Integer Program and using the Branch and Bound technique should also be investigated, as that could lead to a dispatching algorithm that is less computationally intensive than what is presented here.

In addition to further examining the optimization technique that the IDDRR program is based on, several other features could be added as future work. First, with TOD pricing becoming a reality, many home appliances such as the washing machine and dishwasher will surely be available with timers or clocks so they can be run at low cost-of-energy times. It would be beneficial to add the scheduling of these delayable loads to the dispatch to further optimize load shifting. Another delayable load, which may be more prevalent in the future and could also double as an ESD at some times of the day, are hybrid or all electric vehicles. The dispatching system could measure the SOC of the automobile battery when it is plugged into the residence and, also knowing when the car will be unplugged via some setting by the owner of the system, could dispatch the energy accordingly. Another option would be to incorporate the charging and discharging of the automobile battery even while it is away from the residence via some data network. This system could coordinate with other local dispatch centers through the regional dispatch to trade energy while the vehicle is away from its specified residence. However, the system would have to know a planned schedule of the vehicle usage to insure the system's owner is not stranded from his or her destination.

Secondly, optimal sizing of the battery and renewable generator should be further researched. Many things were learned here in regards to the optimum size of the battery and generator, but much of that was by trial and error. Also, many more simulations could be run with the dispatching algorithm presented here with different generators, battery systems, loads, resources, and rates to learn even more about how this algorithm can be best utilized. Simulating systems with very dynamic TOD pricing, such as that which is currently being used by utilities such as Ameren Illinois (available online at https://www2.ameren.com/RetailEnergy/realtimeprices.aspx) gives very different dispatching schedules such as that shown in Figures 6.1 and 6.2.

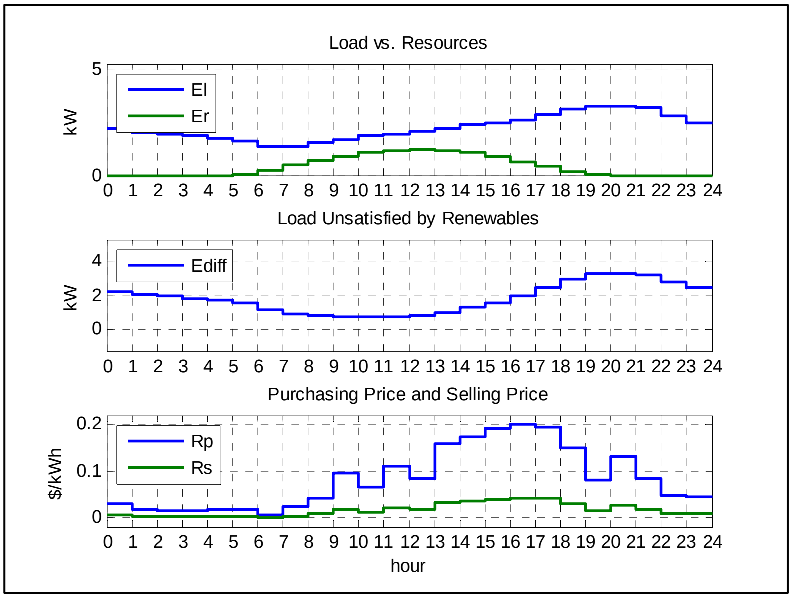

Figure 6.1: Load Resources, and Rates based on Ameren IL TOD Pricing from a single day in July 2008

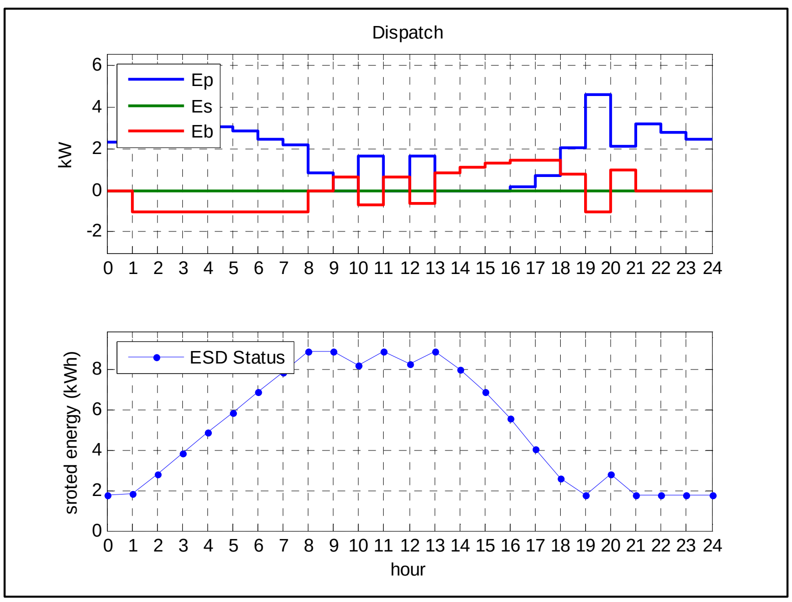

Figure 6.2: Dispatch Schedule based on Ameren IL TOD Pricing from a single day in July 2008

Furthermore, it should be kept in mind that the IDDRR algorithm is only for the power flow dispatching on the lowest level of a multi-tiered hierarchy. The controlling algorithms for the upper tiers of the system hierarchy must be developed and each level must be able to work with the neighboring levels. Also, each tier should be able to adjust the constraints of the tier below it to optimize the entire system. The regional level, for example, should be able to force the local levels to spread out the dispatching of excess energy during peak loads so that the entire peak is reduced, not just the beginning. However, this could also be done in a roundabout way by changing the selling and purchasing prices in each hour of the day and for each customer.

In Closing

While there are many additions and re-developments that could be done with the IDDRR Algorithm, this formulation of it is a very solid initial step that makes distributed renewable energy production much more applicable to a typical person's lifestyle. The IDDRR Algorithm could even be implemented in the real world for the economic benefit of both the owners of renewable energy systems and the electric provider serving them, should the cost of energy storage come down in the future.

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Appendix A - 20 Year Net Present Value Calculations

The equations below summarize the various ways the NPV of the system has been calculated in comparison to operating another form of the system.

Renewable Generator with ESD system and Dispatching Algorithm vs. No Renewable Generator or ESD System (DRE vs. None)

1. The monthly saving of using the system is calculated for each month as follows.

$$\begin{array}{c} \textit{Monthly Savings of DG} \\ \textit{and Dispatchable ESD} \\ \textit{System} \end{array} = \left(\begin{array}{c} \textit{Daily cost of purchasing} \\ \textit{energy without DG or} \\ \textit{ESD System} \end{array} - \begin{array}{c} \textit{Daily cost of purchasing} \\ \textit{energy with DG and} \\ \textit{Dispatchable ESD System} \end{array} \right) \times \begin{array}{c} \textit{Number of} \\ \textit{Days in the} \\ \textit{Month} \end{array}$$

2. The yearly savings are computed by summing monthly savings.

$$\begin{array}{c} \textit{Yearly Savings of DG and} \\ \textit{Dispatchable ESD System} \end{array} = \sum_{month=1}^{12} \left(\begin{array}{c} \textit{Monthly Savings of DG and} \\ \textit{Dispatchable ESD System} \end{array} \right)$$

3. The 20 year net present savings of the DG / Dispatchable ESD system is found as follows.

$$\begin{array}{c} \textit{20 Year Net Present Savings of DG} \\ \textit{and Dispatchable ESD System} \end{array} = \begin{array}{c} \textit{Yearly Savings of DG and} \\ \textit{Dispatchable ESD System} \end{array} \times \textit{(P/A, i\%, n)}$$

$$\text{where,}\quad \begin{cases} \textit{(P/A, i\%, n) = Uniform Series Present Worth} = \dfrac{(1+i)^n - 1}{i(1+i)^n} \\ \\ i\% = 0.08 \\ \\ n = 20 \end{cases}$$

4. The 20 year net present costs of DG / Dispatchable ESD System are also found.

$$\begin{array}{c}\textit{20 Year Net Present costs of DG and} \\ \textit{Dispatchable ESD System}\end{array} = \sum_{year=1}^{n} \left(\textit{Costs in year i} \times \textit{(P/F, i\%, n)} \right)$$

$$\text{where,}\quad \begin{cases} \textit{(P/F, i\%, n) = Single Payment Present Worth} = (1+i)^{-n} \\ \\ \textit{Costs in year i include battery replacement costs if necessary} \end{cases}$$

5. The 20 year net present value of the system is found.

$$\begin{array}{c}\textit{20 Year Net} \\ \textit{Present Value}\end{array} = \begin{array}{c}\textit{20 Year Net Present Savings of DG} \\ \textit{and Dispatchable ESD System}\end{array} - \begin{array}{c}\textit{20 Year Net Present costs of DG} \\ \textit{and Dispatchable ESD System}\end{array} - \begin{array}{c}\textit{Initial Cost of} \\ \textit{the System}\end{array}$$

Renewable Generator Only vs. No Renewable Generator or ESD System (R vs. None)

1. The monthly saving of using the system is calculated for each month as follows.

$$\text{Monthly Savings of DG} = \left(\text{Daily cost of purchasing energy without DG or ESD System} - \text{Daily cost of purchasing energy with DG}\right) \times \text{Number of Days in the Month}$$

2. The yearly savings are computed by summing monthly savings.

$$\text{Yearly Savings of DG} = \sum_{month=1}^{12}\left(\text{Monthly Savings of DG}\right)$$

3. The 20 year net present savings of the DG system is found as follows.

$$\text{20 Year Net Present Savings of DG System} = \text{Yearly Savings of DG System} \times (P/A,\ i\%,\ n)$$

where,

$$(P/A,\ i\%,\ n) = \text{Uniform Series Present Worth} = \frac{(1+i)^n - 1}{i(1+i)^n}$$

$$i\% = 0.08$$

$$n = 20$$

4. There are no periodic costs associated with just the DG system

5. The 20 year net present value of the system is found.

$$\textit{20 Year Net Present Value} = \textit{20 Year Net Present Savings of DG System} - \textit{Initial Cost of the System (Generator Only)}$$

Renewable Generator with ESD system and Dispatching Algorithm vs. Renewable Generator Only (DRE vs. R)

1. The monthly saving of using the system is calculated for each month as follows.

$$\mathit{Monthly\ Savings\ of\ Dispatchable\ ESD\ System} = \left(\mathit{Daily\ cost\ of\ purchasing\ energy\ with\ DG\ only} - \mathit{Daily\ cost\ of\ purchasing\ energy\ with\ DG\ and\ Dispatchable\ ESD\ System}\right) \times \mathit{Number\ of\ Days\ in\ the\ Month}$$

2. The yearly savings are computed by summing monthly savings.

$$\mathit{Yearly\ Savings\ of\ Dispatchable\ ESD\ System} = \sum_{month=1}^{12} \left(\mathit{Monthly\ Savings\ of\ Dispatchable\ ESD\ System} \right)$$

3. The 20 year net present savings of the Dispatchable ESD system is found as follows.

$$\mathit{20\ Year\ Net\ Present\ Savings\ of\ Dispatchable\ ESD\ System} = \mathit{Yearly\ Savings\ of\ Dispatchable\ ESD\ System} \times (P/A,\ i\%,\ n)$$

$$\text{where, } \begin{cases} (P/A,\ i\%,\ n) = \mathit{Uniform\ Series\ Present\ Worth} = \dfrac{(1+i)^n - 1}{i(1+i)^n} \\ i\% = 0.08 \\ n = 20 \end{cases}$$

4. The 20 year net present costs of Dispatchable ESD System are also found.

$$\textit{20 Year Net Present costs of Dispatchable ESD System} = \sum_{year=1}^{n} \left(\textit{Costs in year i} \times \textit{(P/F, i\%, n)} \right)$$

$$\textit{where,} \quad \begin{cases} \textit{(P/F, i\%, n) = Single Payment Present Worth} = (1+i)^{-n} \\ \\ \textit{Costs in year i include battery replacement costs if necessary} \end{cases}$$

5. The 20 year net present value of the system is found.

$$\textit{20 Year Net Present Value} = \textit{20 Year Net Present Savings of Dispatchable ESD System} - \textit{20 Year Net Present costs of Dispatchable ESD System} - \textit{Initial Cost of the System}$$