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A Cost Benefit Analysis of Using a Battery Energy Storage System (BESS) Represented by a Unit Commitment Model

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A Cost Benefit Analysis of Using a Battery Energy Storage System (BESS) Represented by a
Unit Commitment Model

by

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A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Electrical Engineering
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DEDICATION

Thank you to my family and friends for being there throughout my studies.

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Thank you to all of the professors at USF for going above and beyond in making this thesis possible. And another “thank you” to everyone at Southern Company that gave me the opportunity and experience to learn about the energy industry. Most of all I want to thank my father for being an amazing role model in my life.

TABLE OF CONTENTS

LIST OF TABLES	iii
LIST OF FIGURES	iv
ABSTRACT	vi
CHAPTER 1: INTRODUCTION	1
CHAPTER 2: EXPLAINING UNIT COMMITMENT.....	5
2.1 Unit Commitment by Lagrange Relaxation.....	8
2.1.1 Model Equations and Setup	8
2.1.2 Step-by-Step Explanation	9
2.2 Explanation of Unit Commitment Model	11
2.2.1 Input Parameters	11
2.2.2 Input Data Parameters.....	12
2.2.3 System Parameters	14
2.2.4 Load Parameters.....	15
2.2.5 Load Data Flowchart.....	17
2.4 Unit Commitment Main Function.....	22
2.4.1 Initialization	24
2.4.2 System Model Description.....	25
2.4.3 Status of Generators and Minimum and Maximum Capacities	26
2.4.4 Oscillation Prevention.....	27
2.4.5 Solving Dual Optimization Problem for P and C with Obtained $L(\lambda)$	27
2.4.6 Solving the Primal Problem with Economic Dispatch	28
2.4.7 Model Modification to Include a Battery.....	30
CHAPTER 3: COST ANALYSIS FOR A BATTERY STORAGE SYSTEM IMPLEMENTATION IN A UNIT COMMITMENT MODEL.....	31
3.1 Cost of Battery Storage System [13][[7]	31
3.2 Simulation Results	32
CHAPTER 4: CONCLUSION AND FUTURE WORK	37
4.1 Conclusion	37
4.2 Future Work	37

REFERENCES	41
APPENDIX A: COPYRIGHT PERMISSIONS	43

LIST OF TABLES

Table 2.1 Unit Commitment Generator Parameters [6].....	12
Table 2.2 System Parameters [6]	14
Table 2.3 Daily Multiplier Indices.....	15
Table 2.4 Hourly Multiplier Indices	16

LIST OF FIGURES

Figure 1.1 FERC Electricity Market Map [12].....	2
Figure 1.2 “U.S. Battery Storage Market Trends”.....	3
Figure 1.3 Storage - Evolution and Revolution on the Electric Grid, 29 Mar. 2018 [5]	4
Figure 2.1 Generator Data Input Flowchart.....	17
Figure 2.2 Load Data Input Flowchart.....	18
Figure 2.3 Load Data Input File.....	20
Figure 2.4 Loadprog.m Function File.....	21
Figure 2.5 Unit Commitment Model Flowchart.....	22
Figure 2.6 Unit Commitment Model Initialization.....	23
Figure 2.7 Load Profile with Battery	30
Figure 3.1 Load Distribution without Battery, Max Load 3000 MW.....	33
Figure 3.2 Load Distribution with the Load Threshold at 2700 MW.....	33
Figure 3.3 Load Distribution with the Load Threshold at 2400 MW.....	34
Figure 3.4 Load Distribution with the Load Threshold at 2200 MW.....	34
Figure 3.5 Difference Between No Battery Load and Load with Battery at 2700 MW Threshold	35
Figure 3.6 Difference Between No Battery Load and Load with Battery at 2400 MW Threshold	35
Figure 3.7 Difference Between No Battery Load and Load with Battery at 2400 MW Threshold	36

Figure 4.1 Power Price Forming [14]38

ABSTRACT

This thesis aims to provide a general overview of a cost and benefit analysis of incorporating a battery energy storage system within unit commitment model.

The deregulation of the electricity market in the U.S. has only been around for the last two decades. With renewable energy and energy storage systems becoming less expensive, a decentralized market scheme is becoming more popular and plausible. The scope of this work is to provide a fundamental understanding of unit commitment and a cost analysis of applying a battery energy storage system to an already established power system.

A battery energy storage system (BESS) was placed within a unit commitment schematic and modeled for a 7 day/168 hour forecast. Three models were generated, two with and one without the battery energy storage device (BESS). The comparison between the three systems was conducted to produce a visual economic justification to the feasibility of a BESS.

CHAPTER 1: INTRODUCTION

Deregulation of the electricity market or electrical power industry over the last couple of decades has created a competitive concept, causing a disruption within the centralized model. Unfortunately, with transmission constraints and the incapability of storing adequate quantities of electric energy, electricity is considered to be a highly volatile commodity. According to DOE report “Statistical data of US department of Energy indicates that in the US,” the average annual volatility of electricity is 359.8% while Natural Gas & Petroleum, Financial, Metals, Agriculture, and Meat are just 48.5%, 37.8%, 21.8%, 49.1% and 42.6%, respectively” [2]. The extreme price volatility has led to establishing trading risk management strategies. A few main events contributing to this are “1998 substantial price volatility of Midwest and 2000 California electricity crisis” [1].

The Electric Power Market can be broken down by region, as shown in Figure 1.1. The wholesale market can be considered as a ‘supplier’ market, where the main ‘players’ in this market are entities that can distribute large sums of power to the retail market. The wholesaler

always wants to dispatch the least expensive generator to supply the required load and this is done through the Unit Commitment Model, see Chapter 2.

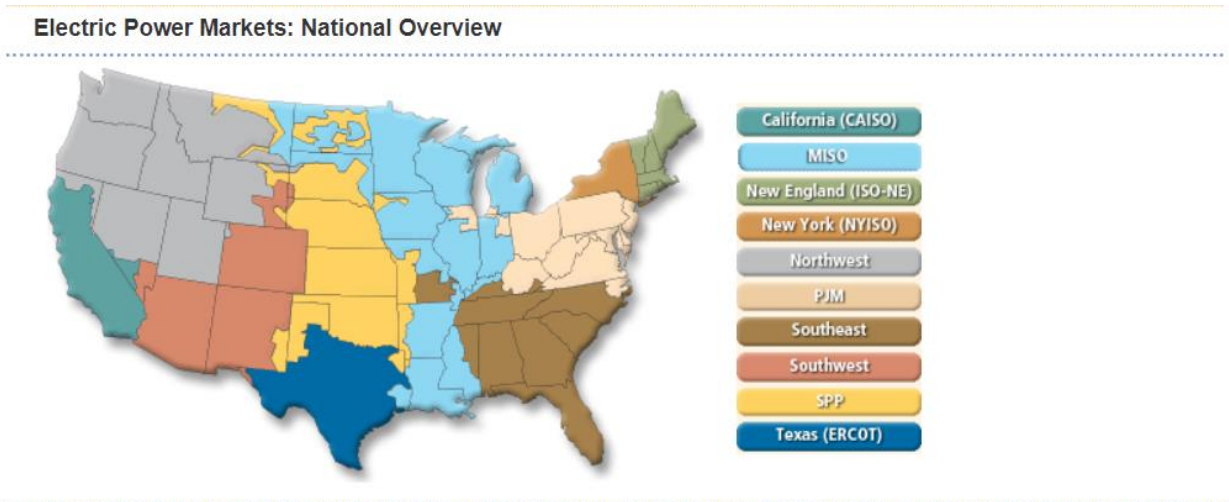


Figure 1.1 FERC Electricity Market Map [12]

The United States have multiple sources of energy, which can be grouped into categories primary and secondary, renewable and nonrenewable. The U.S.'s primary energy sources consist of fossil fuels (this includes petroleum, natural gas, and coal), nuclear energy, and renewable sources of energy. Electricity is produced from all of these sources, thus it is considered a secondary source. The main primary energy consuming sector is the Electric Power sector, which generates most of the electricity for the U.S. The primary energy production in 2017 was Natural gas 31.8%, Petroleum 28.0%, Coal 17.8%, Renewable energy 12.7%, and Nuclear electric power 9.6%. This would mean that 77.6% of the U.S. primary energy production in 2017 was comprised of fossil fuels. Coal production peaked in 2008 and has drastically decreased over the last decade, for two main reasons: Natural gas exploitation and Environmental Protection Agency (EPA) laws (zero emission goal). In year 2017, energy production from wind and solar reached record highs of 12.7%, as mentioned earlier [3].

Figure ES1. U.S. large-scale battery storage capacity by region (2003–2017)

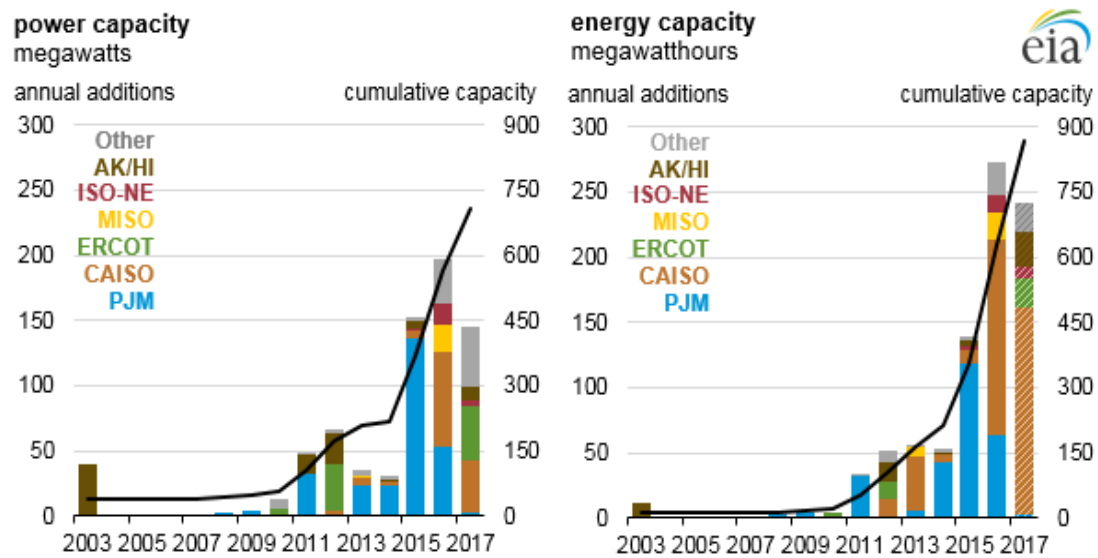
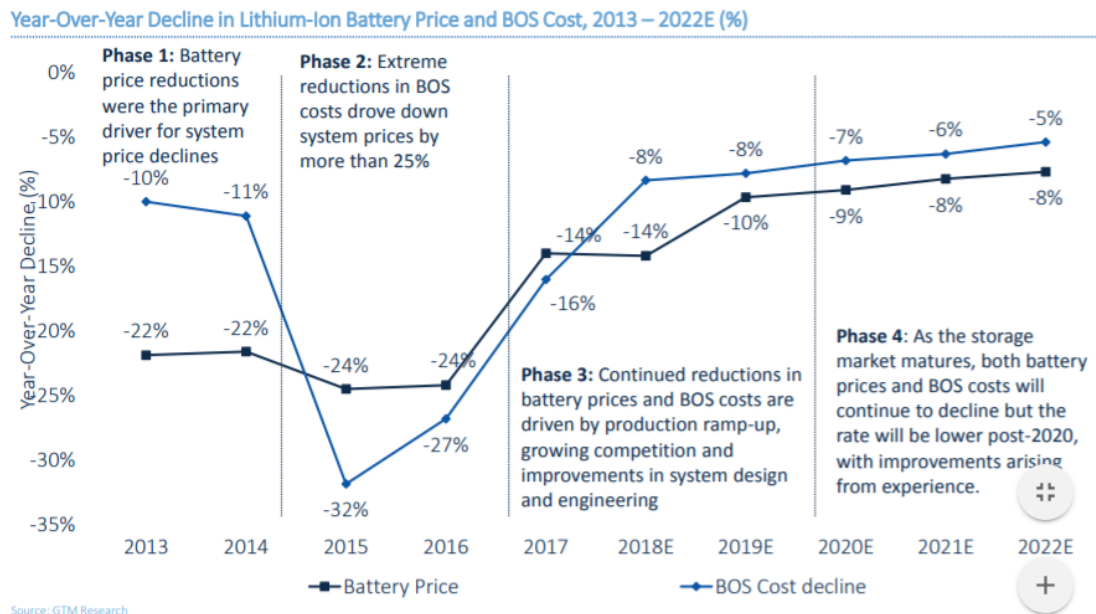


Figure 1.2 “U.S. Battery Storage Market Trends”. [4]

Renewable energy sources are intermittent. Solar energy is produced when there is sunlight and wind energy is produced when there is wind. Sunlight is attained during the day, during peak hours, while majority of wind occurs during the night. This has led to negative localized marginal pricing (LMP), which is considered the nodal price of a ‘unit’ of generation. For simplicity, the LMP is the price of the ‘energy.’ The reason for a negative LMP is that too much energy is generated and oversupplied. The basis of wind energy generation comes from wind turbines. Sometimes it is more cost effective to sell wind-generated electric energy at a loss than turn off a wind turbine, therefore leading to a negative LMP. Fortunately, large electric energy storage (EES) devices with high power density, such as EES batteries, are becoming more viable. Based on Figure 1.2, we can see that the overall usage of large-scale battery storage capacity has increased over the years at an exponential rate.

Annual Declines in Battery Price and Balance-of-System Costs Will Drop Below 10% After 2020



Ravi Manghani, GTM Research: Energy Storage - Evolution and Revolution on the Electric Grid

gtmresearch 11

Figure 1.3 Storage - Evolution and Revolution on the Electric Grid, 29 Mar. 2018 [5]

The main factors for bringing down the cost of battery storage systems is research and the industrial usage of the battery storage technology. As it can be seen in Figure 1.3, battery prices and system costs are in a declining trend since year 2015.

The main motivation for this work is the need for renewable energy sources and energy (battery) storage devices incorporated in a traditional energy generation, transmission and distribution (GT&D) system, and the financial impact of such a system. Global warming and pollution increase, fossil fuels becoming potentially scarcer, and renewable and battery technology advances and costs decrease, have presented an opportunity for this thesis.

CHAPTER 2: EXPLAINING UNIT COMMITMENT

Generators operate at different efficiencies and can be very costly when operated during inefficient intervals. Instead of running cost ineffective generators needlessly, people have come up with a method to optimize electric generation. An electric load must always be matched by power generation. As mentioned earlier, electricity cannot be stored and therefore must be forecasted. If forecasting errors or unexpected generator shut downs, ‘forced outages,’ occur then power outages would occur throughout the system. In such situations, ‘load shedding’ may occur, which means that certain customers do not receive electricity in order to keep the system stable. “Economic dispatch is a method of optimization, but the purpose of economic dispatch is to find the optimum operating policy of a set number of generating units, N_{gen} ” [6]. Unit commitment (UC) is similar to economic dispatch, but it takes into account that there may be a different number of units available and the demand forecast. With these additional factors taken into consideration, an optimum operating policy for every hour of the day can be established. Generators have different cost functions and, by fine tuning their operation or, more coarsely, switching them on and off, an optimal economic dispatch can be achieved for every hour, which is known as “Real-time trading/operation.” Trading can also be conducted on a daily basis, known as “Day-Ahead.” This is due to the fluctuations of electricity usage throughout the day, also known as ‘cycles.’

UC can be looked at as a mathematical optimization problem. Common constraints within UC are spinning reserve, thermal generator constraints (minimum up time and minimum

down time), start-up costs, hydro constraints, generator “Must Run” constraints, and fuel constraints. Spinning reserve is the rapid availability of power generation to cover the loss for one or more generators that may go offline [6]. Thermal generator constraints minimum up and down time are the minimum times required to keep the unit on and off, respectively [6]. Start-up cost is the energy cost that is required to bring a generator online [6]. For example, fuel would be needed to start a turbine, most turbines cannot be accelerated too fast, and so they must burn fuel before reaching the required speed. Hydro constraints are usually associated with dams. When releasing water from a dam you need to be conscious of the water levels. Releasing too much water within a short period of time can cause water levels to go above flood banks. In addition, the water taken from the lake or river would cause water levels to drop, which impacts others requiring the water level. Dams have a very large environmental impact, which enables a lot of political influence [7]. Generator “Must Run” constraints are usually associated with two aspects, reactive power concerns and economic feasibility [6]. Generator reactive power is the main factor to voltage instability [8]. “Managing the reactive power flow in addition to real power flow becomes a very important task for operators to ensure voltage stability throughout the system. In general terms, decreasing a supply of reactive power to the system causes voltage to fall while increasing it causes voltage to rise. A voltage collapse occurs when the system serves a transient load that has a higher reactive power demand than the system can supply” [9]. Generators with large start-up costs or long minimum run times, but with low cost of energy production, such as nuclear power plants, may be termed as must runs, but is still very subjective [10]. Fuel constraints are associated with the ability for the generator to receive the fuel. A generator receiving fuel is usually limited to the pipeline that it is receiving it from [6].

Currently, the most common techniques used for solving UC problems are the Priority-list Schemes, Dynamic Programming (DP), Lagrange Relaxation (LR), and Integer Programming (IP) [6]. Priority-list Scheme solution is simply creating a priority list of units. The priority list could be obtained by “enumeration of all unit combinations at each load level” or by “taking the full-load average production cost of each unit, where the full-load average production cost is simply the net heat rate at full load multiplied by the fuel cost” [6]. DP solution is done by taking cost paths over a time period (trajectories) [6]. DP was originally developed by Dr. Richard Bellman and his associates in the 1950s, which “greatly reduced the computational effort in finding optimal trajectories or control policies” [6]. Unfortunately, like the Priority-list Scheme solution this method still took up large computational power. This method is fine with a few generators, but when a large fleet of generators are needed to optimize this becomes a very troublesome method. The only way to reduce processing time and computational power is to eliminate certain paths, which will cause inaccuracies, and most likely lead away from the most optimal path.

Lagrange Relaxation (LR) is a method of unit commitment that overcomes the difficulties associated with the dimensionality problem of DP. With LR, it is no longer required to conduct ‘brute’ enumerations or cutting paths to reduce computing power, instead mathematical optimization is conducted find an optimal result. The benefit of this method is the objective function. The unit limits, along with the unit minimum up and down time constraints, are separable. This means that whatever is done to one unit will not affect the cost of running another unit. On the other hand, the loading constraint is a coupling constraint. This means that what is done to one unit will affect the other units if there is a load to be met. In order for the LR to be conducted we need to ‘relax’ (ignore) the loading constraint. This is done by using the *dual*

optimization method. In order to maximize the Lagrangian function, Lagrange multiplier λ (lambda), has been adjusted for each generator. In order to minimize the Lagrangian, the generators' 'P' (power generation) and 'U' (on/off factor) values has also been adjusted. The adjusted lambdas from the maximizing process had been acted upon as fixed variables, then, when minimizing the fixed lambdas has been used, the load constraints have been ignored. This is done repeatedly through an iteration approach, until an optimal result has been found [6].

2.1 Unit Commitment by Lagrange Relaxation

2.1.1 Model Equations and Setup

This section explains the system model equations and setup for the dual optimization procedure.

$$U_i^t = 0 \text{ if unit } i \text{ is off - line during period } t \quad (1)$$

$$U_i^t = 1 \text{ if unit } i \text{ is on - line during period } t \quad (2)$$

$$\text{Loading Constraint: } P_{load}^t - \sum_{i=1}^{N_{gen}} P_i^t U_i^t = 0 \text{ for } t = 1 \dots T \quad (3)$$

$$\text{Unit Limits: } U_i^t P_i^{min} \leq P_i^t \leq U_i^t P_i^{max} \text{ for } i = 1 \dots N_{gen} \text{ and } t = 1 \dots T \quad (4)$$

$$\text{Objective Function: } \sum_{t=1}^T \sum_{i=1}^{N_{gen}} [F_i(P_i^t) + \text{Start up cost}_{i,t}] U_i^t = F(P_i^t, U_i^t) \quad (5)$$

N_{gen} is the number of generators and T is the time period under consideration. The dual optimization procedure's goal is to take into account the system model constraints and reach the optimum values by maximizing the Lagrangian, with respect to the Lagrange multipliers, while minimizing in respect to other variables which will be considered as Eq. 6:

$$\text{Lagrange Function: } \mathcal{L}(P, U, \lambda) = F(P_i^t, U_i^t) + \sum_{t=1}^T \lambda^t \left(\sum_{i=1}^{N_{gen}} P_i^t U_i^t \right) \quad (6)$$

$$q^*(\lambda) = \max_{\lambda^t} q(\lambda) \quad (7)$$

$$q(\lambda) = \min_{P_i^t, U_i^t} \mathcal{L}(P, U, \lambda) \quad (8)$$

There are two steps involved to this procedure and they are:

- 1) Step 1: Find a value for each λ^t which moves $q(\lambda)$ toward a larger value in Eq. 7.
- 2) Step 2: Resulting λ^t are taken as fixed values from step 1 and now the minimum of \mathcal{L} needs to be found by adjusting the values of P^t and U^t in Eq. 6.

2.1.2 Step-by-Step Explanation

This section will provide the step by step explanation to the dual optimization procedure.

$$\mathcal{L} = \sum_{t=1}^T \sum_{i=1}^{N_{gen}} [F_i(P_i^t) + Start_up_cost_{i,t}] U_i^t + \sum_{t=1}^T \lambda^t (P_{load}^t - \sum_{i=1}^{N_{gen}} P_i^t U_i^t) \quad (9)$$

The beginning summation operator of Eq. 9 is the summation over time and the second operator is the summation of generators, $F_i(P_i^t)$ is the production cost of the generator,

$Start_up_cost_{i,t}$ is the start up cost of the generators, U_i^t is the on/off factor, and

$\sum_{t=1}^T \lambda^t (P_{load}^t - \sum_{i=1}^{N_{gen}} P_i^t U_i^t)$ is the sum of loading constraints. It can be seen that

$\sum_{t=1}^T \lambda^t (P_{load}^t - \sum_{i=1}^{N_{gen}} P_i^t U_i^t)$ can be broken down and Eq. 9 can be rewritten as:

$$\mathcal{L} = \sum_{t=1}^T \sum_{i=1}^{N_{gen}} [F_i(P_i^t) + Start_up_cost_{i,t}] U_i^t + \sum_{t=1}^T \lambda^t P_{load}^t - \sum_{t=1}^T \sum_{i=1}^{N_{gen}} \lambda^t P_i^t U_i^t \quad (10)$$

Before continuing, it can be noted that $\sum_{t=1}^T \lambda^t P_{load}^t$ is a constant and therefore can be dropped. The reason behind this is that λ^t is fixed. Now that there are only two sums that are being used, the Eq. 10 can be rewritten as:

$$\mathcal{L} = \sum_{i=1}^{N_{gen}} (\sum_{t=1}^T \{ [F_i(P_i^t) + Start_up_cost_{i,t}] U_i^t - \lambda^t P_i^t U_i^t \}) \quad (11)$$

This could be considered the most important step of the procedure. The reasoning behind this is that we can view the internal time summation:

$$\sum_{t=1}^T \{ [F_i(P_i^t) + Start_up_cost_{i,t}] U_i^t - \lambda^t P_i^t U_i^t \} \quad (12)$$

This goes over every time step without the need of considering more than one generator. Now Eq. 11 is free to be minimized without the worry of other variables. As it was mentioned previously, it can be solved for each generating unit individually.

Now that the equation has been restructured the minimum values for each generating unit over all time periods can be found, which will obtain the minimum value of the Lagrangian [6].

This is represented in Eq. 13:

$$q(\lambda) = \sum_{i=1}^{N_{gen}} \min \sum_{t=1}^T \{ [F_i(P_i^t) + Start_up_cost_{i,t}] U_i^t - \lambda^t P_i^t U_i^t \} \quad (13)$$

This is a subject to the constraints:

$$U_i^t P_t^{min} \leq P_i^t \leq U_i^t P_t^{max} \text{ for } t = 1 \dots T \quad (14)$$

In addition to generating on/off constraints there are the up- and down- constraints. The constraints are labeled as S_i , start-up cost for unit i . This is represented through dynamic programming, since there are only two possible states $U_i^t = 0$ or 1 . This is also referred to in more detail later. The minimum of the function can be found by taking the first derivative and setting it equal to zero:

$$\frac{d}{dP_i^t} [F_i(P_i) - \lambda^t P_i^t] = \frac{d}{dP_i^t} F_i(P_i^t) - \lambda^t = 0 \quad (15)$$

resulting in:

$$\frac{d}{dP_i^t} F_i(P_i^{opt}) = \lambda^t \quad (16)$$

This brings about three constraints or concerns that need to be noted. They are:

$$\text{If } P_i^{opt} \leq P_i^{min}, \text{ then } \min[F_i(P_i) - \lambda^t P_i^t] = F_i(P_i^{min}) - \lambda^t P_i^{min} \quad (17)$$

In this case, P_i^{opt} is forced to a minimum value, P_i^{min} .

$$P_i^{min} \leq P_i^{opt} \leq P_i^{max}, \text{ then } \min[F_i(P_i) - \lambda^t P_i^t] = F_i(P_i^{opt}) - \lambda^t P_i^{opt} \quad (18)$$

$$P_i^{opt} \geq P_i^{max}, \text{ then } \min[F_i(P_i) - \lambda^t P_i^t] = F_i(P_i^{max}) - \lambda^t P_i^{max} . \quad (19)$$

In this case, P_i^{opt} is forced to a maximum value, P_i^{max} .

At each time step the equation is minimized ($t=1, \dots, T$). This means that U will be set to 1 if $[F_i(P_i) - \lambda^t P_i^t] < 0$ and 0 if $[F_i(P_i) - \lambda^t P_i^t] \geq 0$. At this point, it has been shown how to schedule generating units at fixed values of λ^t . Eq. 17 represents how to adjust the lambdas:

$$\lambda^t = \lambda^t + \left[\frac{d}{d\lambda} q(\lambda)\right] \alpha \quad (20)$$

where α is a multiplier that is considered as a tuning constant for the gradient. When $\frac{d}{d\lambda} q(\lambda)$ is positive then $q(\lambda)$ will increase and so α can be given a value to let the gradient increase. When $\frac{d}{d\lambda} q(\lambda)$ is negative then α is given a much lower (reduced) value to keep the gradient from increasing.

2.2 Explanation of Unit Commitment Model

The unit commitment model of an eleven-generator power transmission system has been borrowed from Power Generation Operation and Control (GPOC) Laboratory User Manual at the Department of Electrical and Computer Engineering, University of Minnesota from July 2014. The model applies RL method with dual optimization including economic dispatch with constraints (EDC). It has been modified to include battery charging and discharging effect on weekly operational cost of the system. The model consists of the input parameters and constraints, load and lambda limit calculation and cost optimization through unit commitment dual problem solution and economic dispatch.

2.2.1 Input Parameters

Unit commitment model input parameters are generated by importing generator, system and load parameter data from MS Excel spreadsheet files.

2.2.2 Input Data Parameters

Table 2.1 Unit Commitment Generator Parameters [6]

Gen Number	Pg	Pmax	Pmin	a_coeff	b_coeff	c_coeff	Fuel Cost	Startup Cost	Ramp Up	Ramp Down	Mindown Time	Minup Time
1	100	800	100	5	4	0.001	1	0	15	15	1	1
2	100	800	100	5	6	0.002	1	0	15	15	1	1
3	80	400	80	20	8	0.0025	1	0	15	15	1	1
4	80	400	80	20	10	0.0025	1	0	15	15	1	1
5	60	300	60	30	10	0.002	1	0	15	15	1	1
6	60	300	60	30	12	0.002	1	0	15	15	1	1
7	50	200	50	40	14	0.0015	1	0	15	15	1	1
8	50	200	50	40	16	0.0015	1	0	15	15	1	1
9	25	100	25	55	15	0.0012	1	0	15	15	1	1
10	25	100	25	55	17	0.0012	1	0	15	15	1	1
11	25	100	25	55	17	0.0012	1	0	15	15	1	1

Table 2.1 represents the unit commitment parameters and constraints for eleven generators of the system. ‘Pg’ is the notation for power generation, with shown initial values. ‘Pmax’ is the maximum power that a generator can produce, which is also referred to as the ‘Maximum Capacity Limit’ of the generator. ‘Pmin’ is the minimum power that a generator can produce, which is also referred to as the ‘Minimum Capacity Limit’ of the generator. All power units are given in MW. The cost of running each generator changes with the amount of power generated, where the cost function for each generator “i” is:

$$Cost(i) = A(i) + B(i) \cdot P_g(i) + C(i) \cdot P_g(i)^2 \quad (21)$$

It is represented by the cost coefficients ‘a_coeff’, ‘b_coeff’, and ‘c_coeff’ in Table 2.1. The fuel cost effect has been left constant and neutral (fuel value of 1) represented by ‘Fuel Cost’ column. The startup cost, represented by ‘Startup Cost’ parameter of the generators has been set to 0, since it is not included in this analysis. Power ramp up and ramp down have been set to 25% and 50% of the unit capacity per hour, respectively. The minimum up and down time represented by ‘Minup Time’ and ‘Mindown Time,’ have been set to 1 hour, which is the time required for a generator to stay ‘on’ and ‘off’ after the turn on or turn off transient, respectively.

2.2.3 System Parameters

Table 2.2 System Parameters [6]

numhours	168	Number of hours for unit commitment
maxpload	3000	Max peak load over the time period in MW
alpha1	0.01	alpha adjust constant 1
alpha2	0.002	alpha adjust constant 2
MaxIter	100	Maximum iterations
gap_error	0.01	Value of duality gap to converge
datadump	1	set this multiplier to 1 for data output or 0 for no output
plotload	1	set plotload to 1 for a plot of the loads for each hour
edc_tolerance	1.00E-09	EDC convergence tolerance
battery_cap	1200	Battery capacity in MWh
maxpbatt	150	Max battery charging and discharging power in MW
battery_eff	80	Battery charging and discharging efficiency in %
Load_threshold	2200	Load threshold for battery discharge
SOC_init	0	Battery initial state of charge in % of battery capacity

Table 2.2 represents the parameters of the system. The number of hours of the unit commitment horizon, ‘numhours,’ is set to 168 which is the number of hours in a week. The max peak load over the time period (168 hours), maximum load of the system, maxpload, is set to 3000 MW. The ‘alpha1’ and ‘alpha2’ are parameters for adjusting the lambdas using Eq. 17. ‘MaxIter’ is the maximum number of iterations that the model will perform. The ‘gap_error’ is the difference between achieved and the value of the final duality gap convergence (usually 0), which is a measure of the ‘closeness’ to the solution. The ‘datadump’ is a binary flag for output values and by setting it to “1” will show the data output, while setting to “0” will provide no outputs. The ‘plotload’ is the

binary flag for a graph or plot of the results which plots every hour of the unit commitment. When set to “1”, there will be an output plot, while set to “0” will avoid plotting. EDC convergence tolerance, ‘edc_tolerance,’ is set to 1.00E-09, is the prespecified tolerance error between the arriving solution and the exact solution (difference between generated power and load) in each UC one-hour iteration step. The measure of duality gap, which will be used as the measure of closeness to the desired optimization solution, is represented in Eq. 19:

$$Dual_gap = \frac{J^* - q^*}{q^*} \quad (20)$$

J^* is the sum of the operating cost for all generators and q^* is the obtained operating cost through the iterations. The operating cost for each iteration can be represented by $q^*(\lambda)$.

2.2.4 Load Parameters

The load parameters are multiplier indices, Table 2.4, which represent a daily trend of load usage for each hour of the day, beginning at hour 0, 12:00 am, in reference to the maximum load and maximum multiplier indices. Table 2.3 shows the load indices for each day. The reason for creating indices is to represent the cyclical daily and weekly usage of electricity.

Table 2.3 Daily Multiplier Indices

DayMult	Day
1	Sunday
1.2	Monday
1.35	Tuesday
1.35	Wednesday
1.4	Thursday
1.6	Friday
1.05	Saturday
1.05	

Table 2.4 Hourly Multiplier Indices

Hour	Load Index
0	3.5
1	3.4
2	3.3
3	3.25
4	3.3
5	3.4
6	3.5
7	3.7
8	3.9
9	4.3
10	4.7
11	5.3
12	5.6
13	5.7
14	5.65
15	5.5
16	5.5
17	5.3
18	5.2
19	5.1
20	5
21	4.4
22	4.2
23	3.7

2.2.5 Load Data Flowchart

The software used to create the unit commitment model was Matlab. The generator, load and system parameters were written in two MS Excel files. Algorithm flowcharts for generator and load data inputs are shown in Figure 2.1 and Figure 2.2, respectively.

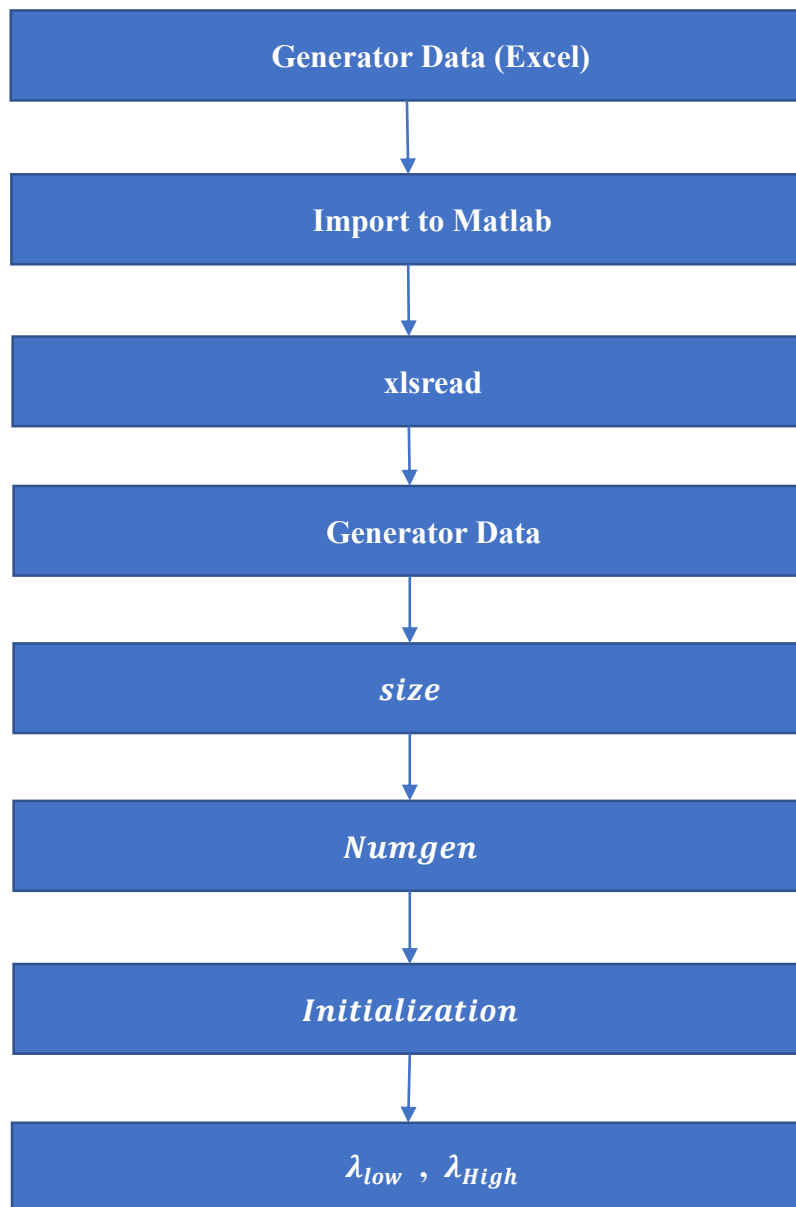


Figure 2.1 Generator Data Input Flowchart

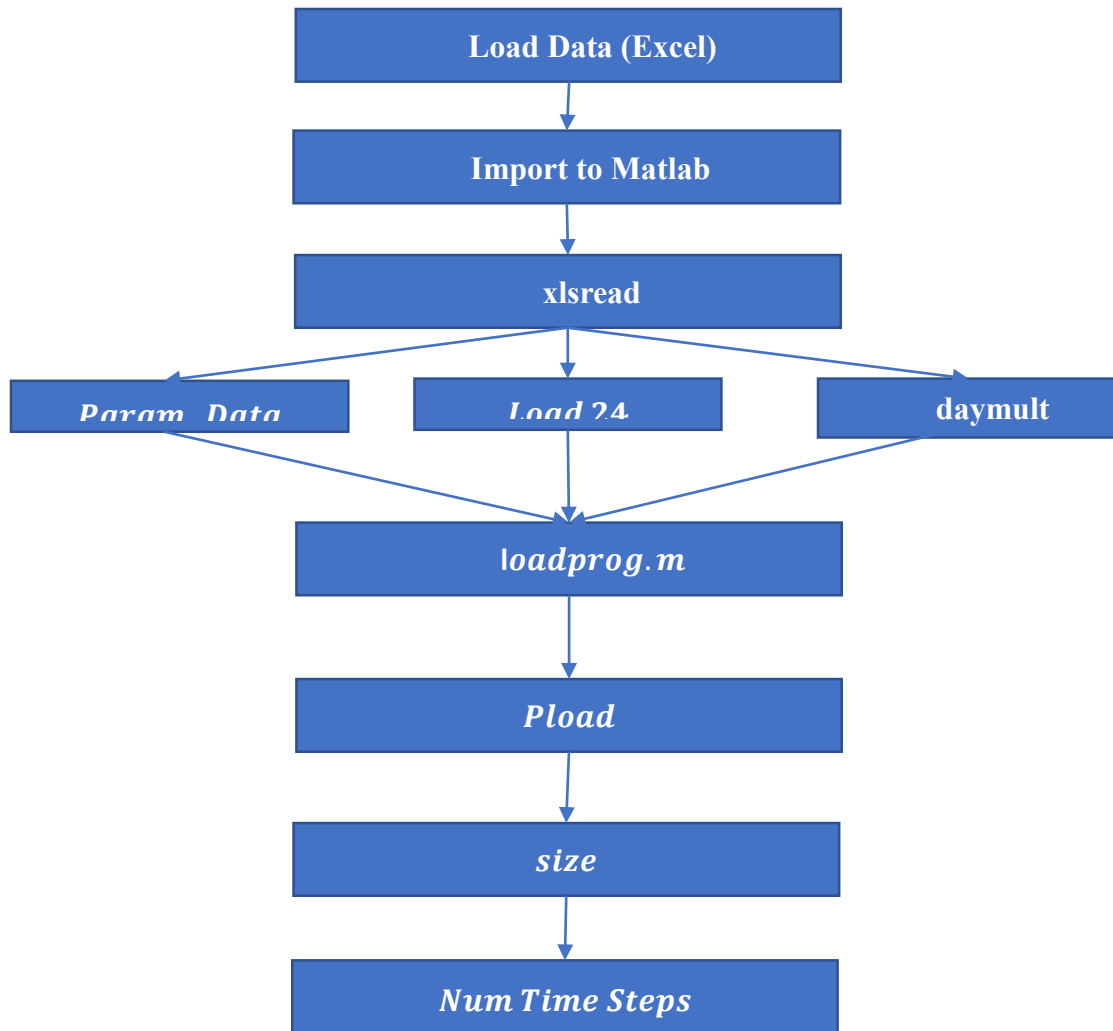


Figure 2.2 Load Data Input Flowchart

Matlab function *xlsread* imports (reads) data from MS Excel file into Matlab files for generator and load data as arrays of corresponding parameter inputs. There are twelve generator parameters imported from Table 2.1. After importing the generator parameters, *size* function counts the total number of generators. Initialization segment sets all parameters to zero before assigning Matlab parameters with values of corresponding array members. Finally, minimum and maximum λ is calculated from the derivative of the cost Eq. 18 at the imported minimum and maximum unit capacity values.

The same *xlsread* function imports from MS Excel load data file into Matlab load parameter input file nine system (simulation) parameters as ‘Parameter_Data’ array from the “Parameter” spreadsheet corresponding to data from Table 2.2, twenty-four hourly indices ‘Load24’ from the “24 Hour Indices” spreadsheet, Table 2.4, and seven daily multipliers ‘daymult’ from “Day Multipliers” spreadsheet, equivalent to Table 2.3. Matlab function *loadprog* is created to calculate maximum values of the day and hour multipliers/indices ‘Maxdaymult’ and ‘Maxloadmult,’ respectively, and one-week load array ‘Pload’ in one-hour increments, based on the load inputs and Eq. 20:

$$P_{load} = load24 \cdot mult \cdot maxpload / (maxloadmult * maxdaymult) \quad (21)$$

The new day multiplier variable ‘*mult.*’ is calculated to ramp up or down after the 16th hour of each day toward the initial value of the following day multiplier to assure continuation of the load curve and mimic the night time rate of change pattern. Otherwise, the *mult* variable, will be assigned a value directly from the day multiplier. The size of the load array determines the total number of time steps (in one-hour increments) in the model simulation.

For clarity, Matlab parameter names are chosen to be the same as the names in MS Excel files. Load data input file is shown in Figure 2.3. Loadprog function file is shown in Figure 2.4.

```

% Input Data File
[file,pathname] = uigetfile('*loaddata.xls*', 'Select Spreadsheet File');
if (pathname == 0),
    error('You Must Select A Valid Data File')
end
S=file;          % Name of the File that we need to read

fprintf(' Case ID: %s \n',file);

[Parameter_data, Parameter_Character_Data] = xlsread(S, 'Parameters');

numhours      = Parameter_data(1);
maxload       = Parameter_data(2);
alpha1        = Parameter_data(3);
alpha2        = Parameter_data(4);
MaxIter       = Parameter_data(5);
gap_error     = Parameter_data(6);
datadump      = Parameter_data(7);
plotload      = Parameter_data(8);
edc_tolerance = Parameter_data(9);

alpha = [alpha1, alpha2];

[load24,Character_Data] = xlsread(S, '24 Hour Indices');
[daymult, Character_Data] = xlsread(S, 'Day Multipliers');

[Pload] = loadprog(load24, daymult, maxload, datadump, plotload);

% Numtimesteps = number of time steps
Numtimesteps=size(Pload,2);

display( ' ' )
display( ' end load input data ' )
display( ' ' )

```

Figure 2.3 Load Data Input File

After the parameter data and characters have been imported by *xlsread* function, two output arguments have been captured. The alpha value was declared as a two-element vector (for

```

function [Pload] = loadprog(load24, daymult, maxpload, datadump, plotload);
%load profile program

maxloadmult = max(load24(:,2));

maxdaymult = max(daymult);

for day = 1:7
    for i = 1:24
        Xplot(i+(day-1)*24)=load24(i,1)+(day-1)*24;
        mult = daymult(day);
        if i>16
            mult = daymult(day)+(((i-16)/8))*(daymult(day+1)-daymult(day));
        end
        Pload(i+(day-1)*24)=load24(i,2)*mult*maxpload/(maxloadmult*maxdaymult);
    end
end

maxpload = max(Pload);

if plotload==1
    figure(01);
    plot(Xplot(1,1:168),Pload(1,1:168),'b-')
end

if datadump==1
    load24
    daymult
    maxloadmult
    maxdaymult
    maxpload
end

```

Figure 2.4 Loadprog.m Function File

adjusting the lambdas). For the nested loops in *loadprog*, the outer loop runs the inner 24-step loop seven times, simulating the seven-day week. To explain the nested loops, the function at the end requires 168 hour iterations, the number obtained by multiplying 24 hours by 7 days. The *Xplot()* creates 168 x-axis independent time points. It takes 24 hours indices from *load24* and adds them to the assigned day.

2.4 Unit Commitment Main Function

The flowchart of the Unit commitment model algorithm is shown in Figure 2.5.

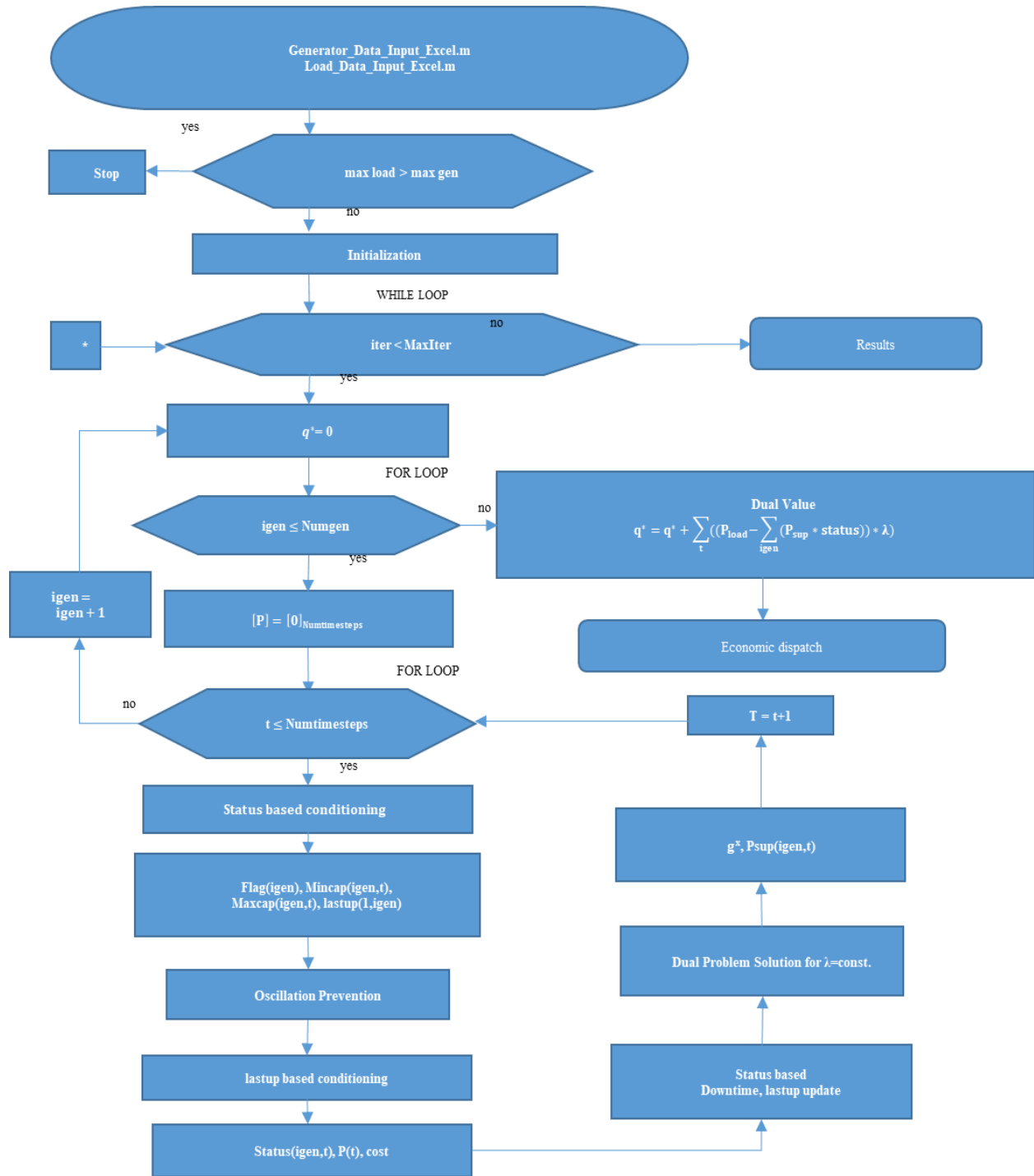


Figure 2.5 Unit Commitment Model Flowchart

Generator_data_input_Excel.m and Load_data_input_Excel.m files are “called” to import generator and load data from MS Excel files. The next part of the flowchart checks if the max load is greater than overall generating maximum capacity. The maximum load cannot be greater than the maximum generation capacity due to NERC requirements. If it is, the program stops. If it is not, the system variables and constraints are initialized next, as it is shown in Figure 2.6.

```

%% Initialization
MaxIter=31;
gap_error=0.1;
edc_tolerance = 1e-9;
lamda=zeros(1,Numtimesteps); %the array of lambdas for each time slot
dual_gap=zeros(1,MaxIter);
Pgen=zeros(Numtimesteps,Numgen);
%av_price=zeros(Numgen,Numtimesteps);

iter=1;
|
%preallocate
flag=zeros(1,Numgen); %indicates a generators ramp down is constrained by the minimum capacity, and it cannot turn off
down_time=zeros(1,Numgen); %for each set, if it is off, how long has it been off?
lastup=zeros(1,Numgen); %for each set, was it running during the last t iteration?
Overconstrained=zeros(1,Numtimesteps); %for each time slot, did we rate limit, not enough or too many gen on
max_committed_capacity=zeros(1,Numtimesteps); %how big can we possibly go with the sets that are on
min_committed_capacity=zeros(1,Numtimesteps); %how low can we possibly go with the sets that are on
total_cost=zeros(1,Numtimesteps); %cost for the EDC
lamdalow=zeros(1,Numgen); %the lambda at the lowest power for a given set
lamdahigh=zeros(1,Numgen); %the lambda at the highest power for a given set
L=zeros(1,Numtimesteps); %lambdas for the EDC
gen_cost=zeros(Numtimesteps,Numgen);
status=zeros(Numgen,Numtimesteps); %whether or not a set is running at a given time slot
Psup=zeros(Numgen,Numtimesteps); %power supplied for each set in each time slot
Maxcap=zeros(Numgen,Numtimesteps); %sets the max capacity for each generator and time step, based on previous Psup and ramp rates
Mincap=zeros(Numgen,Numtimesteps); %sets the min capacity for each generator and time step, based on previous Psup and ramp rates
plotdata=zeros(MaxIter,4);

lambdaoffset=.04; %this is another method to help remove unit commitment oscillations

```

Figure 2.6 Unit Commitment Model Initialization

2.4.1 Initialization

The Initialization section begins with setting the maximum number of iterations, $MaxIter=31$. The duality gap error is defined as $gap_error=0.1$. The economic dispatch tolerance is defined as $edc_tolerance = 1e-9$. The lambda array is defined as $lambda=zeros(1,Numtimesteps)$. The duality gap error is defined as $dual-gap=zeros(1,MaxIter)$. The power generation is defined as $Pgen=zeros(Numtimesteps, Numgen)$. The unit commitment optimization iterations begin with a value of 1, defined as $iter=1$. The *flag* variable indicates if there is a change of value for the ramp down. The generator is constrained by the minimum capacity, so that it cannot turn off. The down time of a generator is the duration of how long the generator must be turned off before it can be turned on again. This array is defined and initialized by $down_time=zeros(1,Numgen)$. If the generator was running during the last iteration is defined by $lastup=zeros(1,Numgen)$. In order to see if there are too many or not enough generators turned on the $Overconstrained=zeros(1, Numtimesteps)$ variable is defined. The $max_committed_capacity=zeros(1,Numtimesteps)$ is a variable that is used for determining the maximum capacity that can be obtained from all generators that are turned on at a given time step. $Min_committed_capacity=zeros(1, Numtimesteps)$ does the same as the $max_committed_capacity$, but for the minimum capacity. The $total_cost=zeros(1, Numtimesteps)$ variable is defined as the total cost for the economic dispatch. The $lambdalow=zeros(1, Numtimesteps)$ variable is for the lowest power generated for an entire set, whereas the $lambdahigh=zeros(1, Numtimesteps)$ variable is for the highest power generated. $L=zeros(1, Numtimesteps)$ is defined as the variable array of Lagrangian multipliers. The $gen_cost=zeros(Numtimesteps, Numgen)$ variable is defined as the variable for the generator costs. The $status=zeros(Numgen, Numtimesteps)$ variable for the status of the generator, if it is

running at the given time slot or not. $P_{sup} = \text{zeros}(\text{Numgen}, \text{Numtimesteps})$ variable is defined as the total power supplied within that given (one-hour) time slot. $Maxcap = \text{zeros}(\text{Numgen}, \text{Numtimesteps})$ variable is defined as the array of the maximum capacities at the time step for each generator and $Minicap = \text{zeros}(\text{Numgen}, \text{Numtimesteps})$ variable is the minimum capacity and time step for each generator. The $plotdata = (\text{MaxIter}, 4)$ variable is a 31 row and 4 column matrix used as a grid structure. $\text{Lambdaoffset} = 0.4$ variable is a variable for an additional method for controlling the unit commitment oscillations. The *tic* command records the time it takes for the function to run.

2.4.2 System Model Description

The main dual optimization routine consists three embedded loops. The outermost loop has pre-determined number ($\text{MaxIter} = 31$) of iterations, which repeat the entire optimization program in order to achieve better convergence of the final dual gap value. Each iteration of this while loop starts with the reset of Eq. 7 to $q^*(\lambda) = 0$. The system math model is based on equations 1-20. The code/model equivalents to equations 1-5 are given next.

On-off status of each generator at each time step is:

$$status_{igen}^t = 0 \text{ if unit } i \text{ is offline at the time step point } t \quad (22)$$

$$status_{igen}^t = 1 \text{ if unit } i \text{ is online at the time step point } t \quad (23)$$

Total generated power must match the load profile at every time step:

$$P_{load}^t - \sum_{igen=1}^{11} P_{igen}^t status_{igen}^t = 0 \text{ for } t = 1 \dots 168 \quad (24)$$

System constraints include status dependent power limits and power rate limits, embedded in calculations of time-variable power limit matrices Minicap and Maxcap :

$$\text{Minicap}_{igen}^t \leq P_{igen}^t \leq \text{Maxcap}_{igen}^t \text{ for } igen = 1 \dots 11 \text{ and } t = 1 \dots 168 \quad (25)$$

Time domain arrays Mincap(t) and Maxcap(t) are calculated iteratively through the innermost time loop for each generator on a way to calculate the full 11x168 constraint matrix.

The objective function is derived from the cost function 18) of each generator:

$$\sum_{t=1}^{168} \sum_{i=1}^{11} [F_i(P_i^t)] U_i^t = F(P_i^t, U_i^t) \quad (26)$$

$$F_i(P_i^t) = A + B \cdot P_i^t + C \cdot P_i^{t2} \quad (27)$$

2.4.3 Status of Generators and Minimum and Maximum Capacities

The content of the relaxed Lagrange method can be divided in two parts:

- 1) Dual value calculation of $q^*(\lambda)$, based on power and cost calculated from operating constraints, such as power ramp, on/off state and capacity limits
- 2) Solving economic dispatch with constraints for the total cost and dual gap values.

The first embedded loop in the “Dual value calculation” part is a generator counting loop for eleven generators. It starts with resetting generated power array to $P=0$ at each time step for each generator (168 array members). Following the reasoning behind Eq. 11 with neglected generator startup cost, the generator counting loop encompasses the time loop.

The time loop has increments of one hour over the course of one week. It is created to calculate current and last-step status-based conditioning of minimum capacity checking binary variable ‘flag’; capacity constraint (11 times 168) matrices ‘Mincap’ and ‘Maxcap,’ dependent on active generator combination at each increment; and binary ‘lastup’ array containing a previous step on/off state of each generator. ‘Mincap’ and ‘Maxcap’ are current-step minimum and maximum capacities of each generator at each given time point (hour of the week). They are initialized by the imported constraints of minimum and maximum capacities of each generator from MS Excel. Later, through the iterations, these variables depend on the previous step power

and ramp limit constraints. When the previous status is ‘on’ ($\text{status}(t-1) = 1$), ‘Mincap’ and ‘Maxcap’ follow equations 27 and 28:

$$\text{Mincap}(igen, t) = P_{sup}(igen, t - 1) - \text{rampdn}(igen) * \text{Maxcap_unit}(igen) \quad (28)$$

$$\text{Maxcap}(igen, t) = P_{sup}(igen, t - 1) + \text{rampup}(igen) * \text{Maxcap_unit}(igen) \quad (29)$$

When the previous status is ‘off’ ($\text{status}(t-1) = 0$), ‘Mincap’ and ‘Maxcap’ follow equations 29 and 30:

$$\text{Mincap}(igen, t) = \text{Maxcap_unit}(igen) \quad (30)$$

$$\text{Maxcap}(igen, t) = \text{rampup}(igen) * \text{Maxcap_unit}(igen) \quad (31)$$

2.4.4 Oscillation Prevention

Oscillation in the algorithm could occur when a generator needs to turn on to meet the minimum capacity, but it doesn’t have λ high enough to do so. The ‘Overconstraint’ flags have been raised at this point and λ has decreased (in a case of too high power) or increased (too low power) by a predetermined λ_{offset} .

2.4.5 Solving Dual Optimization Problem for P and C with Obtained $L(\lambda)$

Generator power and cost variable arrays, as well as the status of each generator for current time step are conditionally calculated depending on the generator on/off status from the previous step, which is indicated by variable array lastup for all generator states. All initial values in this array values are set to ‘on’ ($\text{lastup}=[1]_{N_{gen}}$) at the first time step and they change based on instantaneous power values of each generator at each time step.

If $\text{lastup}(igen)=1$, following Eq. 16, the generated power from generator ‘igen’ in the generator counting loop is calculated from the first derivative of Langrangian function, Eq. 8, of the cost given in Eq. 18:

$$P(t) = (\lambda - B(igen))/(2 \cdot C(igen)) \quad (32)$$

$P(t)$ of each generator is limited/constrained by corresponding 'Mincap' and 'Maxcap' variables calculated in the previous step by Eq. 27-30. The Cost is, then, calculated by Eq. 18. Beside the 'flag' binary variable described in Section 2.6.4, the on/off status of the generator depends on the difference between the calculated cost and $\lambda \cdot P(t)$ product. If the difference is negative, the generator should keep running. Otherwise, it should stop.

If $lastup(igen)=0$, its status would depend on the downtime duration, which should exceed the minimum downtime constraint. If it does, the power is calculated by Eq. 31 and startup cost would be added to the cost Eq. 18. The same difference condition applies to the generator status. If it doesn't the status is off ($status(igen)=0$) and the cost is equal zero. $Lastup$ and downtime variables get updated/conditioned based on the status for the next iteration, while the dual value $q^*(\lambda)$ gets updated by adding the calculated cost to the sum of the costs calculated in previous steps of the generator counting loop. When the two-loop iterations are complete, the dual value of the current step of the dual optimization loop can be calculated according to Eq. 7:

$$q^*(\lambda, iter) = q^*(\lambda, iter - 1) + \sum_t (P_{load}(t) - \sum_{igen} (P(igen, t) \cdot status(igen, t)) \cdot \lambda) \quad (33)$$

where $iter = 1, \dots, MaxIter$; $t = 1, \dots, 168$; $igen = 1, \dots, 11$. It was set $MaxIter = 32$.

2.4.6 Solving the Primal Problem with Economic Dispatch

In order to converge to an optimal solution of the dual optimization problem, a new Lagrangian multiplier λ is calculated at the economic dispatch part of each optimization loop step and applied to the Dual Value calculation in the new iteration.

The economic dispatch procedure starts with opening the time loop and updating the committed capacity constraints at each time step and imposing them as cost clamps, making the cost inapplicable high value if either one of these constraints has been reached. This situation would prevent further execution of the economic dispatch part of the code. Otherwise, λ

calculation procedure continues with calculating its limits from Eq. 16 and Eq. 31 by replacing $P(t)$ with $Mincap$ and $Maxcap$ constraints and calculating the total minimum and maximum of λ :

$$\lambda_{low}(igen) = 2 \cdot C(igen) \cdot Mincap(igen) + B(igen) \quad (34)$$

$$\lambda_{high}(igen) = 2 \cdot C(igen) \cdot Maxcap(igen) + B(igen) \quad (35)$$

$$\lambda_{min} = \min(\lambda_{low}(igen)) \quad (36)$$

$$\lambda_{max} = \max(\lambda_{high}(igen)) \quad (37)$$

The goal is to reach λ with a minimum error from the optimal solution. Consequently, a new variable is introduced and initialized for at each time step to:

$$\Delta\lambda = \frac{\lambda_{max} - \lambda_{min}}{2} \quad (38)$$

A new iterative loop, embedded in the time loop, has been established to minimize error between the load and total supplied power at each time step. It has been achieved by manipulating $L(\lambda)$ and, consequently, generated power from each generator, by increasing or decreasing $L(\lambda)$ by $\Delta\lambda$, at the end of each iteration, depending on the sign of calculated and updated load-supplied power difference. This loop has been limited to 200 iterations in this code. After closing this loop, the total generated power cost has been updated for the current time step. This would close the time loop iterative calculations.

Finally, the total cost has been calculated and compared dual value $q^*(\lambda)$ to calculate a relative error using Eq. 17:

$$\text{dual gap}(\text{iter}) = \frac{\text{total cost} - q^*(\lambda)}{q^*(\lambda)} \quad (39)$$

If the dual gap oscillations occur, a fine tuning using α -parameters is performed. This would conclude the economic dispatch part and encircle the entire calculation cycle of each dual optimization loop iteration. If dual gap reaches the gap error from Figure 2.6, the economic dispatch loop breaks and no further optimization is necessary.

2.4.7 Model Modification to Include a Battery

Battery model has been treated as a positive or negative addition to the load during battery charging and discharging periods, respectively. Consequently, only load data input file and *loadprog* function had to be modified. The battery is charged over eight hours from the minimum charge to full charge. Since the absolute battery state of charge is irrelevant for this analysis, the minimum charge has been considered as 0% charge and the maximum charge has been considered as 100% charge. Charging occurs only after each battery discharge. Battery charging and discharging efficiency of 80% each has been included in the model. Battery discharge occurs only if a new, pre-determined, load threshold has been reached. The equivalent one-week load profile with battery charging and discharging action included is shown in Figure 2.7.

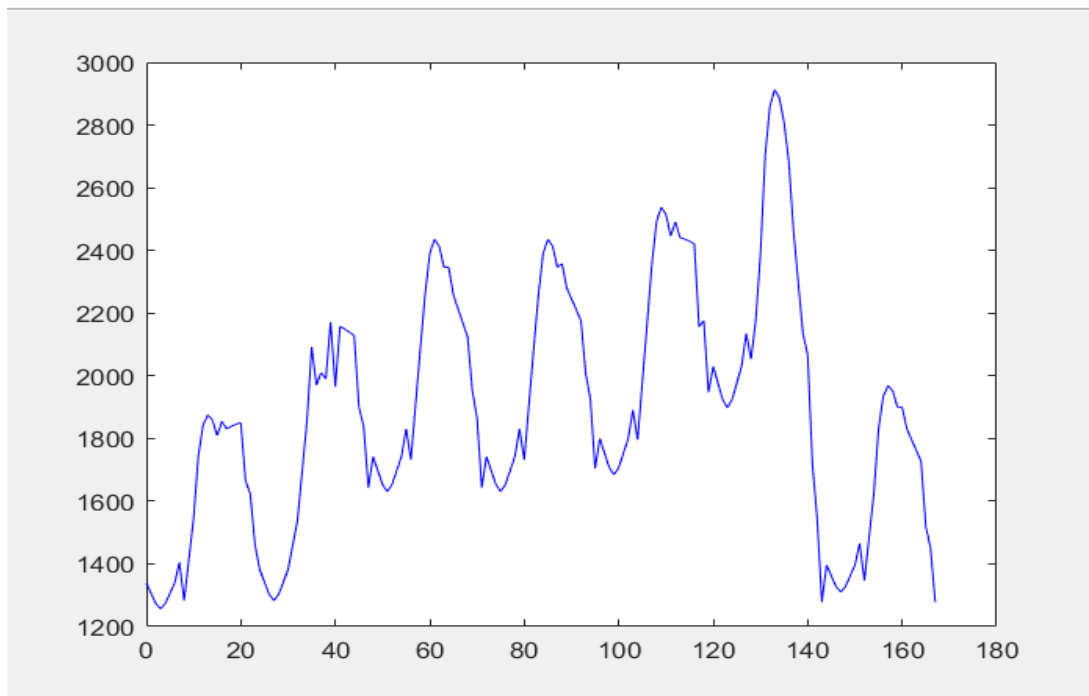


Figure 2.7 Load Profile with Battery

CHAPTER 3: COST ANALYSIS FOR A BATTERY STORAGE SYSTEM IMPLEMENTATION IN A UNIT COMMITMENT MODEL

3.1 Cost of Battery Storage System [13] [7]

The capital cost used in this paper will be limit to three parameters (equations 19, 20, 21):

The cost of the storage unit is:

$$Cost_{storage}(\$) = Unit\ Cost_{storage} \left(\frac{\$}{kWh} \right) * E(kwh) \quad (40)$$

All systems have some inefficiency factor (η) hence:

$$Cost_{storage}(\$) = Unit\ Cost_{storage} \left(\frac{\$}{kWh} \right) * (E(kwh)/\eta) \quad (41)$$

Used Li-Ion batteries are usually sold at 80% efficiency, thus $\eta = 0.8$.

The cost of the Power Conversion System is:

$$Cost_{pcs}(\$) = Unit\ Cost_{pcs} \left(\frac{\$}{kW} \right) * P(kW) \quad (42)$$

The Total Cost is:

$$Cost_{pcs}(\$) = Cost_{pcs} \left(\frac{\$}{kW} \right) + Cost_{storage}(\$) \quad (43)$$

When, the unit costs of the subsystems are known, and the storage capacity in kW is known, it is possible to rewrite the total cost in terms of the power rating:

$$Cost_{system}(\$/kW) = Cost_{total}(\$)/P(kW) \quad (44)$$

A new 15 kWh battery pack currently costs \$990/kWh to \$1,220/kWh and is projected to cost between \$360/kWh to \$440/kWh by 2020 [13]. This would elute to a cost of \$14.85 million

for a 150 MWh battery storage system. If we take the projected cost (year 2020) of \$360/kWh then the cost of a 150 MWh battery storage system would be \$5.4 million.

3.2 Simulation Results

Load distribution between the generators are shown in Figure 3.1 to Figure 3.4. The analysis was done by subtracting the costs of every hour between the 3000 MW threshold (No battery) system to the 2200, 2400, and 2700 MW systems. The resulting graphs can be seen in Figure 3.5 to Figure 3.7. The overall cost of the 3000 MW system was \$2,158,942. On the other hand, the cost of the 2200, 2400, and 2700 MW systems were \$2,173,853, \$2,170,320, and \$2,171,224, respectively. The battery was set to charge for 8 hours during the lowest cost hours (off-peak) and discharge during the highest peaks (on-peak). The capacity of the battery was set to a max discharge/charge of 200 MW and a total capacity of 800 MWh. The thresholds determined when the battery would output.

An interesting observation to take note of is that the 2400 MW system had the lowest cost compared to the other thresholds. One might expect the 2700 MW threshold to obtain the most return as it is set to discharge at the highest peak load. Although, this may seem logical, the unit commitment path can present different results. Each generator has a different cost function. Greatly lowering the usage of one generator may not decrease the costs as much as slightly lowering the usage of multiple generators and vice-versa. In the 2200 MW scenario, see Figure 3.4, the battery was used too candidly and did not make the maximum cost reductions that it could. The exact opposite happened during the 2700 MW scenario, see Figure 3.2. The battery was held to discharge at a very high peak load and was used one day of the entire week, resulting in a large opportunity loss. Looking at the 2400 MW scenario, see Figure 3.3, the battery storage system discharges over a peak period of time that lowers the expensive generator usage.

Generators 4 through 9 are all used much less than in the other scenarios, which was the main resulting factor to being more cost effective. It can be noted that the battery energy storage system can be further optimized by discharging it during expected expensive generator usages.

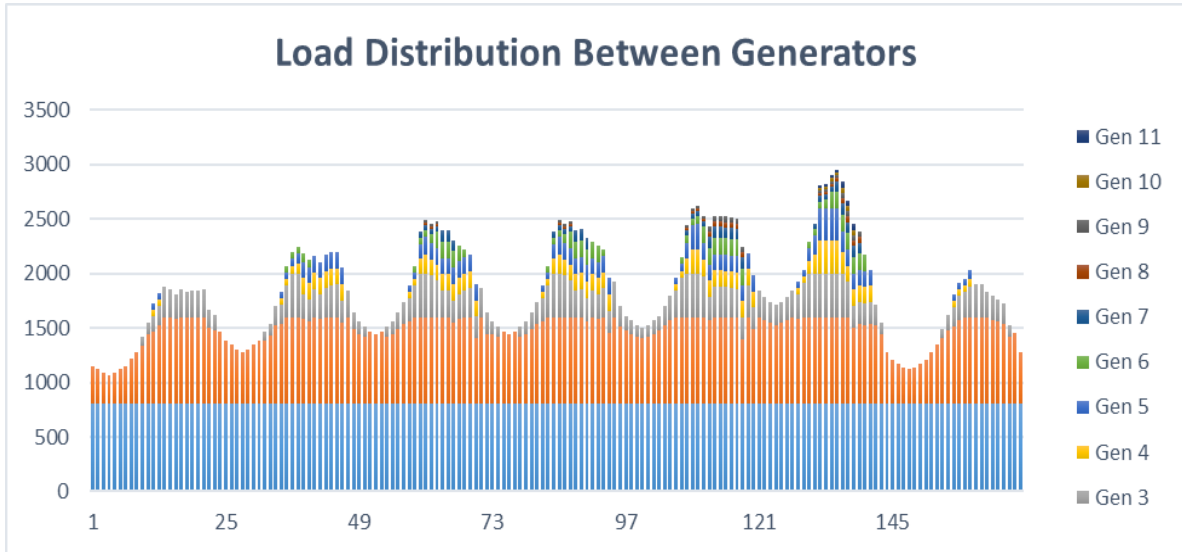


Figure 3.1 Load Distribution without Battery, Max Load 3000 MW

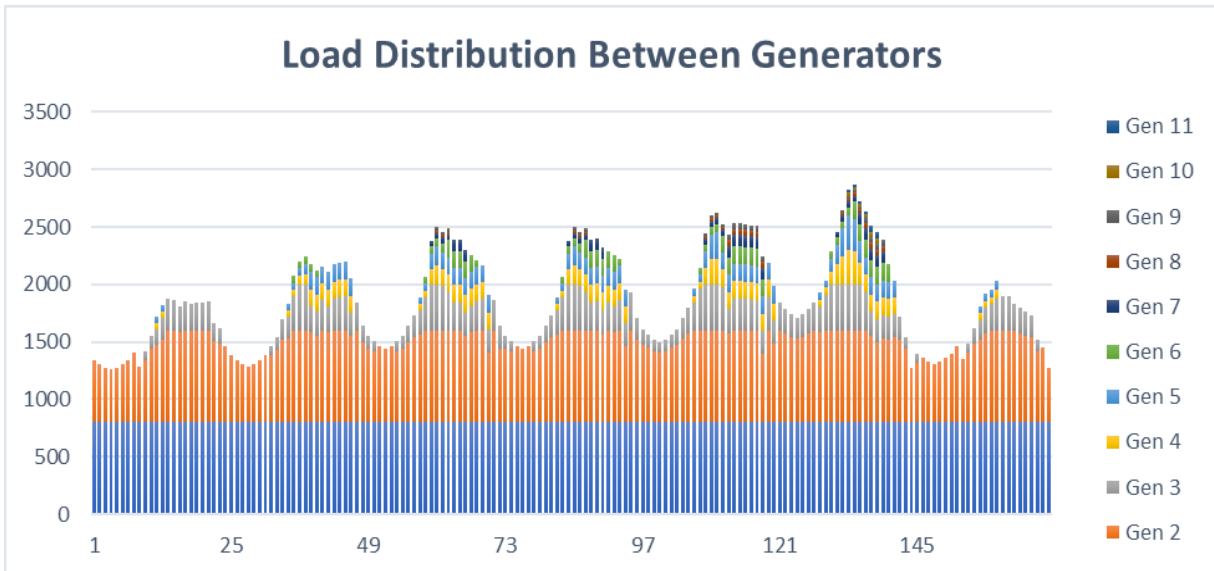


Figure 3.2 Load Distribution with the Load Threshold at 2700 MW

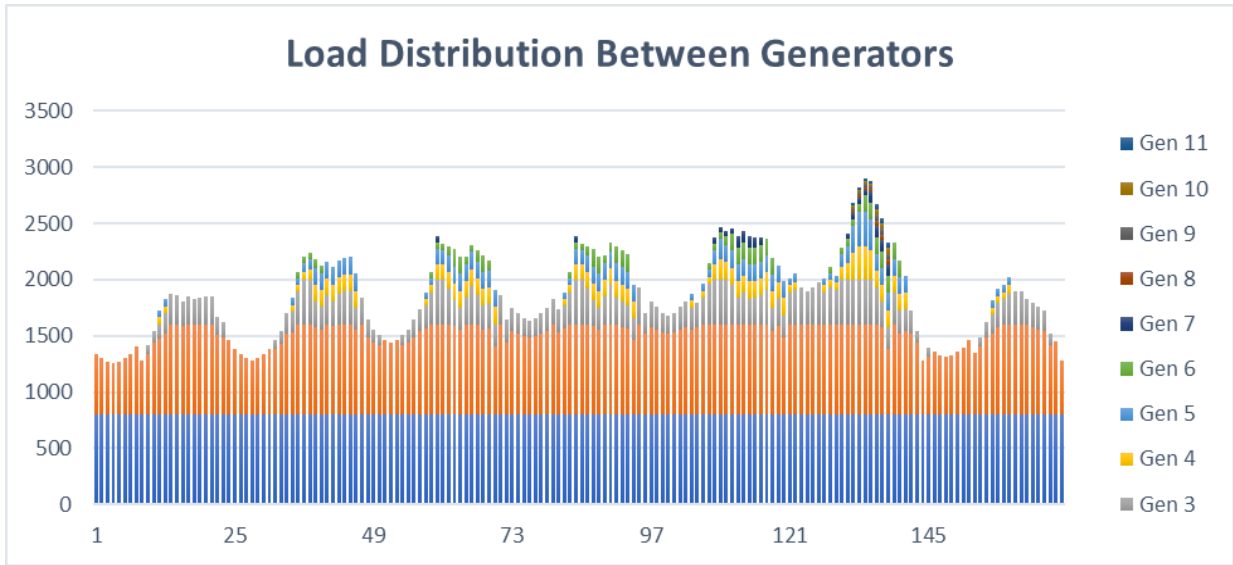


Figure 3.3 Load Distribution with the Load Threshold at 2400 MW

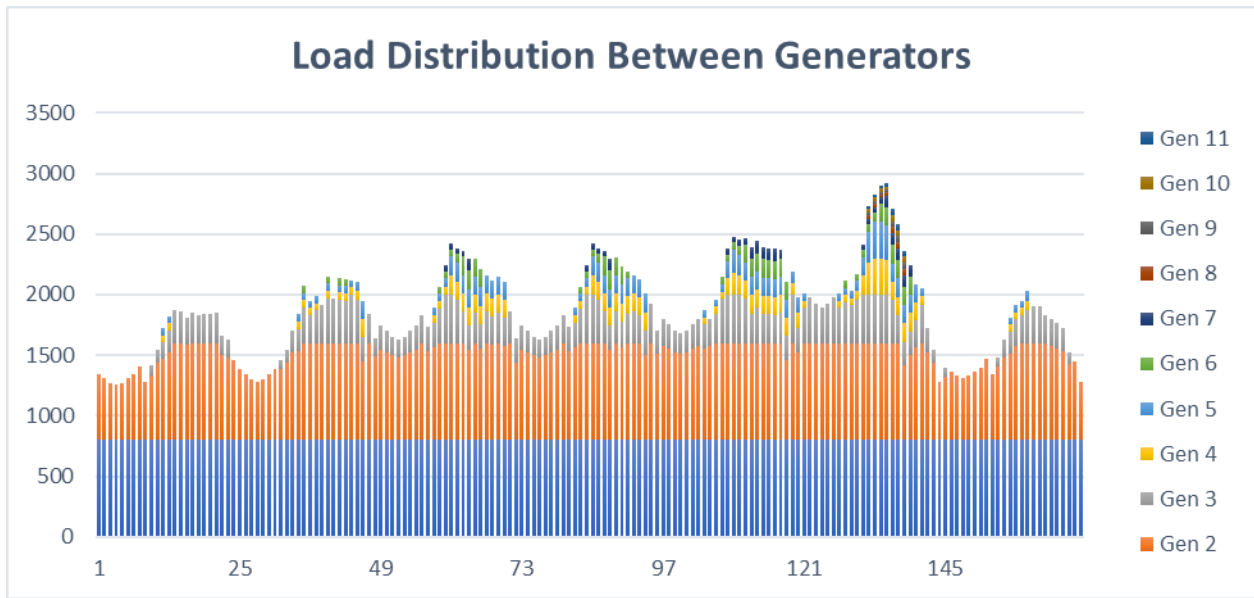


Figure 3.4 Load Distribution with the Load Threshold at 2200 MW

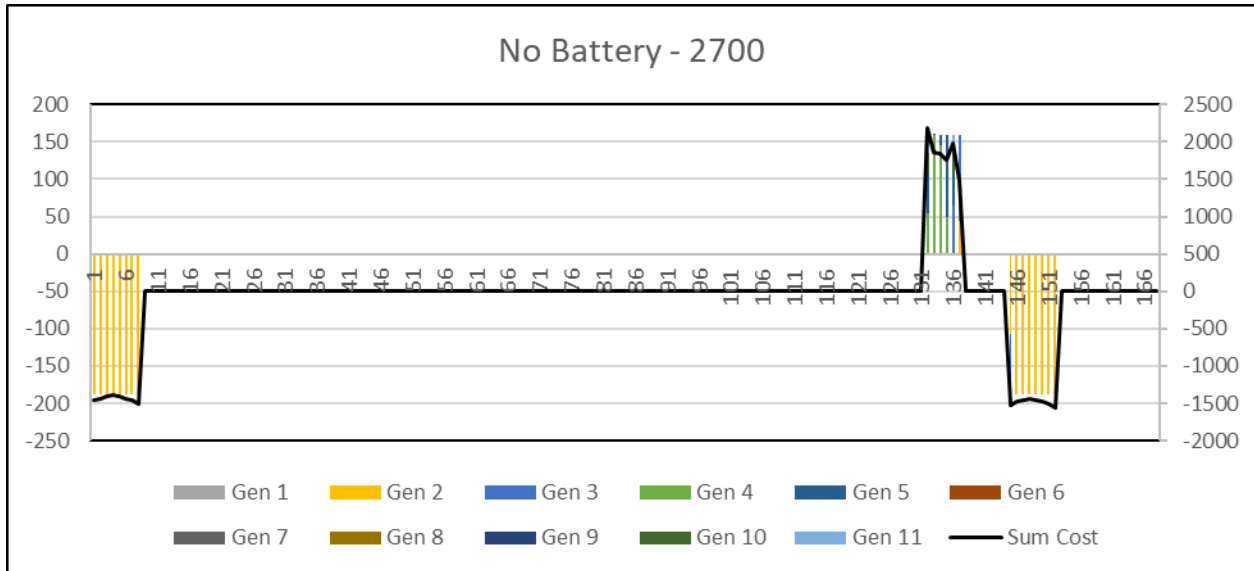


Figure 3.5 Difference Between No Battery Load and Load with Battery at 2700 MW Threshold

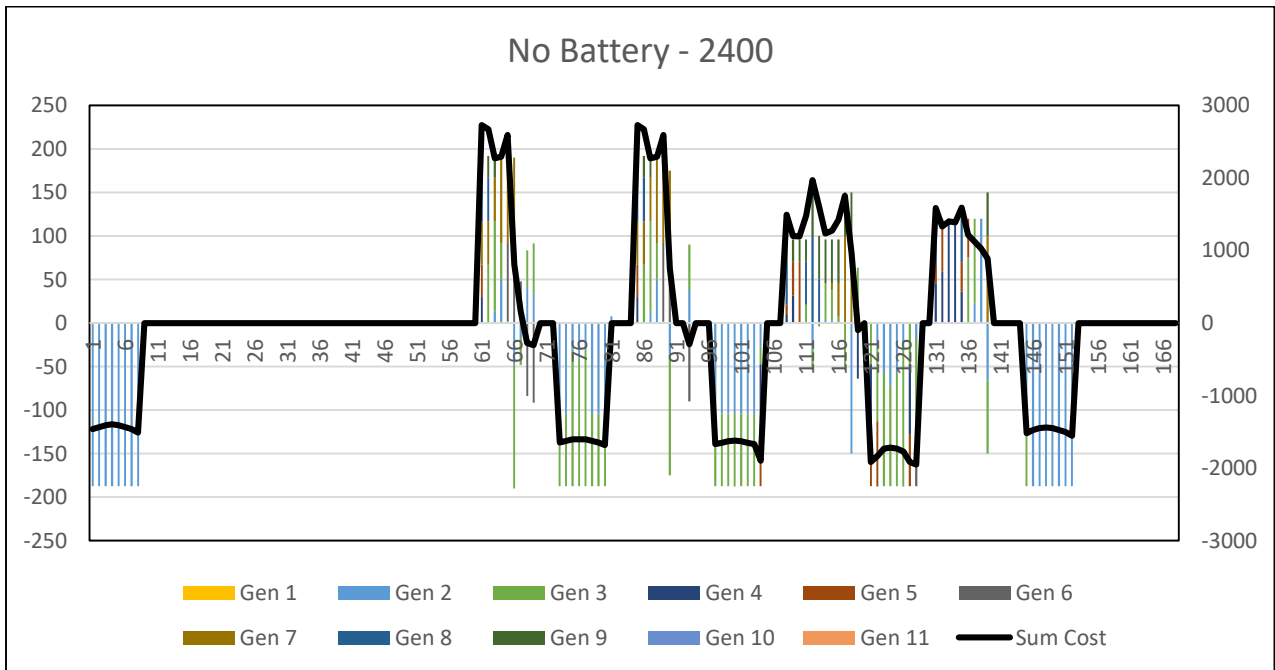


Figure 3.6 Difference Between No Battery Load and Load with Battery at 2400 MW Threshold

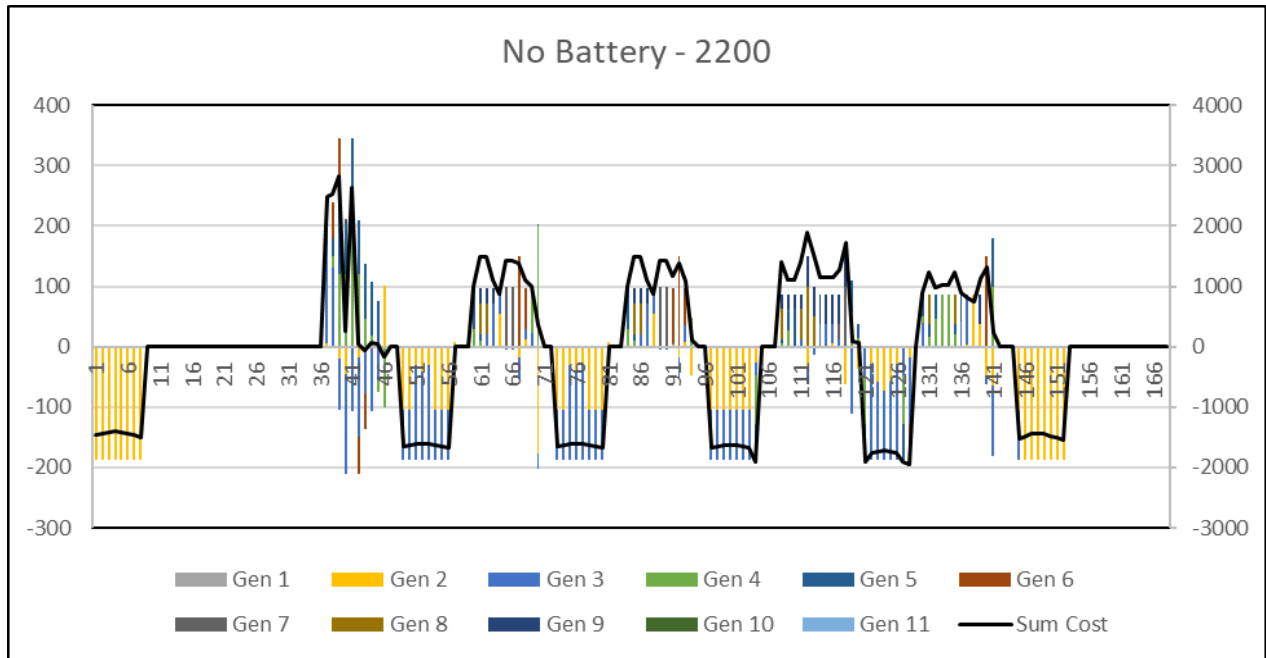


Figure 3.7 Difference Between No Battery Load and Load with Battery at 2400 MW Threshold

CHAPTER 4: CONCLUSION AND FUTURE WORK

4.1 Conclusion

The results show that the cost of using a battery energy storage system is not economically justifiable. This is somewhat to be expected as battery energy storage systems are the newest and most expensive method to store energy. If the difference between the off peak and on peak hours were much greater, then using a battery energy storage system might be a possibility. Unfortunately, this does not account for installation and maintenance costs, which lowers the feasibility of using a battery energy storage system. If the efficiency of a BESS increases, while fuel prices increase, then a BESS might become economically feasible.

4.2 Future Work

Energy markets can be broken down into three groups [11] as it is shown in Figure 4.1:

- 1) Fuels: oil, gas, coal, and their derivatives and byproducts
- 2) Electricity
- 3) Weather, emissions, pulp and paper, and forced outage insurance

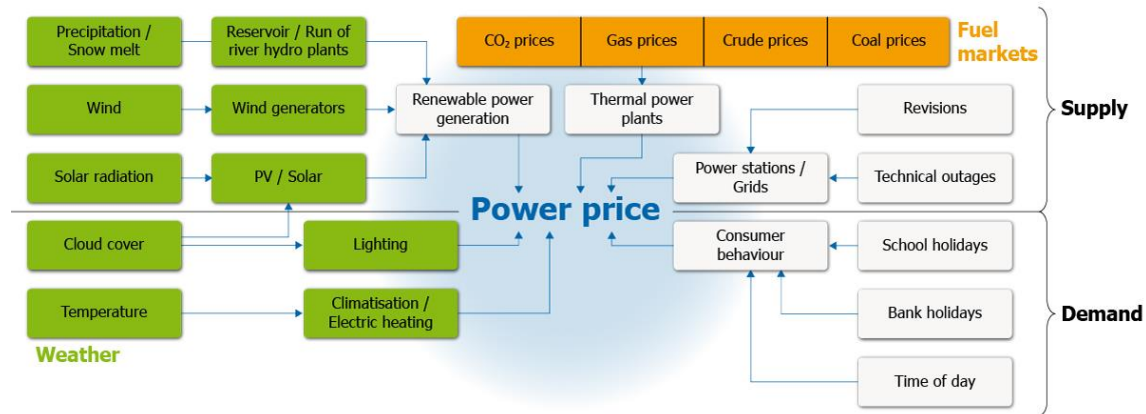


Figure 4.1 Power Price Forming [14]

This chapter will dwell into Electricity market. It is important to briefly mention that the cost coefficients of the unit commitment model can be affected by all three groups of the energy market (for further reading see reference [11]).

The electricity market trades on a Day-ahead (DA) and Hour-ahead (HA) basis. The DA market transacts the generation of electricity for the next day. The HA market transacts the generation of electricity for the next hour [11]. The structure of this market somewhat correlates with the “need for real-time balancing of locational supply and demand” [11]. Because supply and demand must always meet instantaneously the supply of electricity can be broken down into three criteria:

- 1) Generation
- 2) Transmission
- 3) Ancillary services (balancing)

Generation and Transmission are fairly straight forward concepts. Ancillary, in simple terms, can be considered as the “back-up” to keeping the grid balanced. There is also a separate market for ancillary services. The ancillary service markets are composed of multiple products.

Some of which are spinning reserves, non-spinning reserves, operating reserve, energy

imbalance, regulation, reactive power supply [11]. Spinning reserves “are available immediately and can be brought to full capacity within ten minutes” [11]. Non-spinning reserves “are available immediately and can be brought to full capacity within ten minutes” [11]. “Operating reserves are resources that can be brought up to full capacity within 30 minutes” [11]. “Energy imbalances are resources that need correcting related to supply and demand” [11]. “Regulation is the reactive energy needed to maintain the phase angle of the system” [11]. “Reactive power supply is the maintenance of the voltage on the transmission lines” [11]. The markets described here are not necessarily markets in every part of the United States or world. An independent system operator (ISO) or Regional Transmission Organization (RTO) have been in place to maintain the system. This paper will mainly consider ISOs. In the United States, these are public utility companies. They are regulated by both the individual states and Federal Energy Regulatory Commission (FERC). This has allowed ISOs to manage the markets/services or allowed bilateral markets to be prevalent enough giving the ISO only a limited role [11]. The cash market operates on a basis of two contracting forms, pools and bilateral. The pool is a “formal establishment of the market (system) clearing price at which all cash (energy) transactions clear” [11]. Examples in the United States would be New England Power Pool (NEPOOL), New York Intrastate Access Settlement Pool (NYPOOL), California Independent System Operator (CAISO), and the Midwest Independent System Operator (MISO). The bilateral market (also known as Over-The-Counter (OTC)) is where “all transactions are entered into by two parties and are independent of any other transactions in the market” [11]. Examples are the Electric Reliability Council of Texas (ERCOT) and Southeastern Electric Reliability Council (SERC). This paper will not cover spatial market, but will provide a basis for work in this area.

Risk Management is the Process of achieving the desired balance of risk and return through a particular trading strategy” [1]. Risk involved with trading electricity can be broken down into several types Regulatory Risk, Credit Risk, Liquidity Risk, Operational Risk, Delivery Risk, and Price Risk [1]. Regulatory risk is the risk associated with the impacts that laws or regulation changes may have on the market sector. Credit risk is risk that the counter party will not meet their obligations as pertained in the agreement. Liquidity risk is the risk that the commodity cannot be turned into cash when needed or desired. Operational risk is the risk remaining after determining financial and systematic risk; prospect of loss from failed internal systems or policies. Delivery risk is the risk that the counterparty will not be able to deliver the underlying asset or cash pertaining to the contract. Price risk is the risk involved with the decline of value of a security.

Risk management within the financial industry can be broken down into two aspects, risk control and risk assessment [1]. The energy industry contains contracts revolving around delivery and non-delivery (financial trading) of commodities. It would be interesting to see the development of a future/forward contract from a unit commitment model that incorporates risk parameters/speculations. Most forward/future contracts within the energy industry do not take into consideration power output (deliverables). As the industry becomes less regulated, it wouldn't be surprising to see a trend of increased neglect in power load to generation matching; while more focus is put on the portfolio aspect of trading. This has the potential to lead to over inflated forward/future contracts.

REFERENCES

1. A Survey on Risk Management in Electricity Markets - IEEE Conference Publication, ieeexplore.ieee.org/document/1709009/references#references. 2. Energy Information Administration, “Derivatives and Risk Management in the Petroleum, Natural Gas, and Electricity Industries,” U.S. Department of Energy, Washington, Tech. Rep, SR/SMG/2002-01, Oct. 2002.
2. “U.S. Energy Facts - Energy Explained, Your Guide To Understanding Energy - Energy Information Administration.” Chinese Coal-Fired Electricity Generation Expected to Flatten as Mix Shifts to Renewables - Today in Energy - U.S. Energy Information Administration (EIA), 16 May 2018, www.eia.gov/energyexplained/?page=us_energy_home.
3. “U.S. Battery Storage Market Trends.” Energy Information Administration, May 2018, www.eia.gov/analysis/studies/electricity/batterystorage/pdf/battery_storage.pdf.
4. Energy Storage - Evolution and Revolution on the Electric Grid, 29 Mar. 2018, www.ncsl.org/Portals/1/Documents/energy/Webinar_energy_storage_Manghani_present_32165.pdf.
5. Wood, Allen J., et al. Power Generation, Operation, and Control. Wiley-Interscience, 2014.
6. 2016 WATER ACTION REPORT. 2016, www.southerncompany.com/content/dam/southern-company/pdf/reports/WaterActionReport2016.pdf.
7. “Generator Reactive Power Limits and Voltage Stability - IET Conference Publication.” Design and Implementation of Autonomous Vehicle Valet Parking System - IEEE Conference Publication, Wiley-IEEE Press, ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=637785.
8. Wildi, Théodore. Electrical Machines, Drives, and Power Systems. Pearson/Prentice Hall, 2006.
9. “Economic Dispatch and Operations of Electric Utilities.” Economic Dispatch and Operations of Electric Utilities | EME 801:www.e-education.psu.edu/eme801/node/532.
10. Eydeland, Alexander, and Krzysztof Wolyniec. Energy and Power Risk Management: New Developments in Modeling, Pricing, and Hedging. Wiley, 2003.

11. “The AMES Wholesale Power Market Test Bed.” AMES Market Package (Leigh Tesfatsion), www2.econ.iastate.edu/tesfatsi/AMESMarketHome.htm.
12. Zagoras, Nikitas. Battery Energy Storage System (BESS): A Cost/Benefit Analysis for a PV Power Station. 2014, www.nrel.gov/grid/assets/pdfs/second_grid_sim_zagoras.pdf.
13. “Press & News.” RWE AG - How the Electricity Price Is Determined, www.rwe.com/web/cms/en/403722/rwe/press-news/how-the-electricity-price-is-determined/.

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