A flexible model for economic operational management of grid battery energy storage

Robert L. Fares^{1,*}, Michael E. Webber¹

Department of Mechanical Engineering, The University of Texas, Austin, Texas 78712

Abstract

To connect energy storage operational planning with real-time battery control, this paper integrates a dynamic battery model with an optimization program. First, we transform a behavioral circuit model designed to describe a variety of battery chemistries into a set of coupled nonlinear differential equations. Then, we discretize the differential equations to integrate the battery model with a General Algebraic Modeling System (GAMS) optimization program, which decides when the battery should charge and discharge to maximize its operating revenue. We demonstrate the capabilities of our model by applying it to lithium-ion (Li-ion) energy storage operating in Texas' restructured electricity market. By simulating 11 years of operation, we find that our model can robustly compute an optimal charge-discharge schedule that maximizes daily operating revenue without violating a battery's operating constraints. Furthermore, our results show there is significant variation in potential operating revenue from one day to the next. The revenue potential of Li-ion storage varies from approximately \$0–1800/MWh of energy discharged, depending on the volatility of wholesale electricity prices during an operating day. Thus, it is important to consider the material degradation-related “cost” of performing a charge-discharge cycle in battery operational management, so that the battery only operates when revenue exceeds cost.

Keywords:

Energy storage, Battery, Economics, Optimization

*Department of Mechanical Engineering, The University of Texas at Austin, 204 E. Dean Keeton Street, Stop C2200, Austin, Texas 78712-1591. +1 (512) 471-7838.

Email address: robertfares@utexas.edu (Robert L. Fares)

1. Introduction

Because of the high cost of conventional large-scale electricity storage technologies (such as pumped-hydro energy storage [1]), it has typically been more economical to produce electricity on demand, generating and then delivering it to the end user in real time. To reliably deliver electricity on demand, generation, transmission, and distribution equipment must have the capacity to serve peak electric load, which only occurs for a small portion of the year. Furthermore, electric generators must set aside reserve capacity for grid ancillary services to ensure electric supply consistently equals demand, even in the case of a contingency. These two aspects of today’s electric grid represent a non-trivial component of the cost of electricity. At the same time, concerns about air pollution, sustainability, and anthropogenic climate change have driven an increase in the amount of intermittent renewable energy resources connected to the grid. Because of the grid’s on-demand design, it would benefit from the integration of more flexible electricity resources as the penetration of intermittent resources increases [2].

Grid energy storage is an appealing technology because it temporally decouples electricity supply from demand, which means generation can occur at a time other than when there is demand. Doing so adds new flexibility to grid operations with the potential to reduce grid capital expenditures, integrate higher fractions of intermittent renewable energy, and increase electric reliability. For these reasons, recent advances in battery technology have driven renewed interest in grid-based battery energy storage. Nevertheless, batteries have only been sparingly implemented on the U.S. electric grid. In 2011, there were less than 140 MW of batteries installed [3]. This fact can be attributed to the high cost of existing battery systems and uncertainty surrounding the revenue potential of battery energy storage operating on the electric grid.

The revenue potential of grid battery energy storage is uncertain for primarily two reasons. First, because a battery cannot store electricity without incurring energy losses and material degradation from electrochemical conversion, the performance and lifetime of a battery in grid applications is uncertain. Second, because an energy storage plant uses grid electricity as its “fuel,” the external price of electricity has a strong effect on its revenue potential. To generate revenue from the sale of electric energy, a grid battery must charge when the real-time price of electricity is low and discharge when the price is high. Thus, the profit maximization problem for a grid

battery system is considerably more difficult than the profit maximization problem for a conventional power plant. For these reasons, it is desirable to develop a tool that integrates two features: 1) a battery model capable of describing complex battery performance characteristics within a real-time control framework, and 2) a decision-making framework to show how a battery should operate to maximize its revenue potential from the sale of electric energy.

To augment the existing literature, this paper connects a behavioral-circuit model capable of describing nonlinear battery performance characteristics with an optimization algorithm for grid battery operational management. The remainder of this paper is organized as follows: Section 2 reviews past literature that has sought to develop models to describe battery performance and manage the operation of grid energy storage. Section 3 discusses how we discretize a dynamic behavioral circuit model from the literature for use with optimization. Section 4 describes the formulation of a model-based optimization problem for operational management of grid battery storage, and application of the model to simulate lithium-ion (Li-ion) battery energy storage used for wholesale energy arbitrage in Texas’ restructured¹ electricity market. Section 5 shows the results of our case study, and discusses the implications of our results for economic operational management of a grid battery. Finally, Section 6 draws conclusions from our results and proposes future work.

2. Background

2.1. Battery modeling

Researchers have developed a number of models to describe a battery. These models can be broadly classified into two major categories: first-principles electrochemical models and empirical behavioral models. First-principles models use physical equations to describe the transport and reaction of active species inside a battery. They describe how the concentration of active species at the electrode surface affects the overpotential required to drive an electrochemical reaction to store or release energy [4, 5, 6, 7, 8]. Empirical behavioral models use mathematical equations or physical analogs

¹Modern competitive electricity markets are often described as “deregulated,” despite the fact that numerous regulations still exist. This work will use the term “restructured” to describe competitive electricity markets.

(e.g. electric circuits) to describe the system-level characteristics of a battery, such as capacity, efficiency and voltage. Peukert’s law, which describes the relationship between rate of discharge and discharge capacity, is one of the earliest empirical models [9, 10]. Other models describe a battery’s non-linear capacity/recovery effects [11, 12, 13, 14], or energy efficiency [15]. Many empirical models use an electric circuit analog to describe the system-level behavior of a battery using a combination of variable voltage sources, resistors, and capacitors. A number of these models have been developed in the literature including Thévenin equivalent circuit models [16, 17, 18], impedance-based models [19, 20, 21], and runtime-based models [22, 23]. More recent electric circuit analog models combine the benefits of many of these models to empirically describe a number of complex battery characteristics [24, 25].

Empirical models are advantageous for real-time battery control because they can be designed to describe complex battery characteristics without significant computational complexity. In particular, electric circuit analog models have proven to be a flexible tool for empirically describing battery performance under diverse operating conditions, including temperature, state of charge, and charge-discharge rate [24, 25, 26, 27, 28, 29]. These models describe a battery’s open circuit voltage using a variable potential source, and then use a combination of series resistors and parallel resistor-capacitor couples to describe a battery’s ohmic potential drop and dynamic voltage behavior at various time scales. Numerous studies have developed methods to experimentally extract the electrical parameters required to describe a battery’s dynamic state using these models [24, 28, 29, 30, 31].

2.2. Operational management of grid energy storage

A number of researchers have sought to analyze the value of electricity storage in the context of restructured electricity markets. Early studies use simple assumptions about energy storage system performance, operating revenue, and cost to assess the value of electricity storage in a restructured electricity market from a largely qualitative perspective [32, 33, 34]. More recent studies utilize multiple years of dynamic electricity price data that have become available since restructured electricity markets opened to quantitatively assess the value of electricity storage [35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48]. Typically, studies focus on assessing the techno-economic performance of one specific technology in a given market and system context using optimization and other techniques for energy storage operational

106 management.

107 A principle limitation of existing studies is that they assume a storage
108 device has a constant roundtrip efficiency, energy capacity, and power capa-
109 bility, regardless of its instantaneous operating state. While this assumption
110 might not have a strong influence on the overall economic assessment of a
111 given energy storage device, it makes it difficult to connect economic assess-
112 ments with real-time control to maximize the daily operating revenue of an
113 energy storage device deployed on the grid. To connect operational manage-
114 ment of grid energy storage with real-time battery control, we develop an
115 optimization model that uses a flexible behavioral circuit model developed
116 previously [24] to describe the dynamic operating state of a grid battery sys-
117 tem and decide how it should charge and discharge to maximize its daily
118 operating revenue without violating its operating constraints.

119 3. Battery model transformation

120 Chen and Rincón-Mora’s model describes the state of a battery using two
121 coupled electrical circuits, as shown in Figure 1 [24]. The “battery lifetime
122 circuit” on the left-hand side of Figure 1 approximates a battery’s state of
123 charge based on the current input, I . The capacitor C_c integrates the charge
124 flowing into and out of the battery to approximate state of charge, and the
125 resistor R_{sd} models the effect of self discharge in the absence of an external
126 charging current or float voltage. The circuit components combine to produce
127 a voltage at node V_{SOC} corresponding to the battery’s state of charge. The
128 “voltage-current characteristics circuit” on the right-hand side of Figure 1 es-
129 timates the behavior of a battery’s terminal voltage, V , based on the current
130 input, I , and state of charge (V_{SOC} from the battery lifetime circuit). The
131 variable potential source $V_{OC}(V_{SOC})$ models how open-circuit voltage changes
132 with state of charge, and the series resistor R_s and two parallel RC networks
133 consisting of $R_{t,s}$, $C_{t,s}$, $R_{t,l}$, and $C_{t,l}$ model how the battery’s terminal voltage
134 dynamically changes under a variable applied current, I , due to the ohmic
135 potential drop and short- and long-term transient reaction dynamics inside
136 the battery. Each of these circuit components has parameters defined by a
137 variable function determined from experimental performance data [24].

138 Researchers have extracted the parameters required to describe the per-
139 formance of a number of different batteries using this model. Chen and
140 Rincón-Mora extracted the model parameters for both Li-ion and nickel-
141 metal hydride (Ni-MH) battery cells under various discharge rates [24]. To

142 model the performance of a larger battery system, Li, et. al. extracted the
 143 model parameters for an Ultralife UBBL10 Li-ion module (consisting of sev-
 144 eral battery cells) under various discharge rates [28, 29]. To model the effect
 145 of temperature on performance, Bauer and Kelder fit the model to a LiFePO_4
 146 based Li-ion battery operating at 0 °C, 25 °C, and 40 °C [26]. Similarly, Kim,
 147 et. al. fit the model to 100 Ah polymer Li-ion cells of various ages operating
 148 at 0 °C, 20 °C, and 40 °C [27].

149 Because the model developed previously [24] has become popular in the
 150 empirical battery modeling literature, we select this model for our analysis.
 151 To discretize the model for the purposes of optimization, we use Kirchoff's
 152 circuit laws to extract the mathematical equations that describe the dynamic
 153 state of the behavioral circuit model components, resulting in the following
 154 nonlinear differential equations:

$$\dot{V}_{SOC} = -\frac{I}{C_c} - \frac{V_{SOC}}{R_{sd}C_c} \quad (1)$$

$$\dot{V}_{t,s} = \frac{I}{C_{t,s}} - \frac{V_{t,s}}{R_{t,s}C_{t,s}} \quad (2)$$

$$\dot{V}_{t,l} = \frac{I}{C_{t,l}} - \frac{V_{t,l}}{R_{t,l}C_{t,l}} \quad (3)$$

$$V = V_{OC} - IR_s - V_{t,s} - V_{t,l} \quad (4)$$

155 where the circuit components C_c , R_{sd} , $C_{t,s}$, $R_{t,s}$, $C_{t,l}$, $R_{t,l}$, R_s , and V_{OC}
 156 are, theoretically, empirical functions of state of charge (V_{SOC}), current (I),
 157 temperature, and cycle number. However, these parameters can typically be
 158 simplified to be independent or linear functions of some variables for specific
 159 batteries [24, 26, 27, 28, 29].

160 To implement Equations 1–4 in an optimization model, we discretize the
 161 equations using a forward-difference approximation. Equations 5–8 approxi-
 162 mate each of the behavioral circuit state variables at time step k of duration
 163 Δt .

$$V_{SOC}(k+1) = \left(-\frac{I(k)}{C_c(k)} - \frac{V_{SOC}(k)}{R_{sd}(k)C_c(k)} \right) \Delta t + V_{SOC}(k) \quad (5)$$

$$V_{t,s}(k+1) = \left(\frac{I(k)}{C_{t,s}(k)} - \frac{V_{t,s}(k)}{R_{t,s}(k)C_{t,s}(k)} \right) \Delta t + V_{t,s}(k) \quad (6)$$

$$V_{t,l}(k+1) = \left(\frac{I(k)}{C_{t,l}(k)} - \frac{V_{t,l}(k)}{R_{t,l}(k)C_{t,l}(k)} \right) \Delta t + V_{t,l}(k) \quad (7)$$

$$V(k) = V_{OC}(k) - I(k)R_s(k) - V_{t,s}(k) - V_{t,l}(k) \quad (8)$$

164 The following section discusses how we integrate the discretized model
 165 given above with an optimization model for economic operational manage-
 166 ment of grid battery energy storage.

167 4. Dynamic economic operational management model

168 A battery energy storage system can provide a number of different grid
 169 applications [37, 49]. Typically, the decision variable for grid operation is
 170 the instantaneous level of charging or discharging power flowing between
 171 the electric grid and the battery device. The charging or discharging power
 172 applied to the battery affects its dependent state variables: current, voltage,
 173 and state of charge, all of which must be controlled within acceptable limits
 174 during battery operation. The following sections implement an optimization
 175 program for optimal storage dispatch, and then demonstrate the capabilities
 176 of the program using the example of Li-ion energy storage providing wholesale
 177 energy arbitrage in Texas' restructured electricity market.

178 4.1. Optimization Model

179 To decide how a grid battery should charge and discharge to maximize its
 180 operating revenue without violating its operating constraints, we implement
 181 the discretized battery model developed in the previous section in a nonlinear
 182 optimization program. The objective function of the optimization program
 183 depends on the intended energy storage application. In its most general form,
 184 the objective function can be written as in Equation 9, with the objective
 185 expressed as a function of the power, P , flowing between the battery and the
 186 grid during each optimization time step, k .

$$\text{Objective} = f(P(k_1), \dots, P(k_n)) \quad (9)$$

187 We relate the optimization decision variables, P , to the dependent state
 188 variables I , V , and V_{SOC} with the equality constraints of Equations 10–14,
 189 which are imposed at each time step, k , to encapsulate the dynamics of the
 190 circuits shown in Figure 1.

$$\forall k \quad P(k) = I(k)V(k) \quad (10)$$

$$\forall k \quad V_{SOC}(k+1) = \begin{cases} V_{SOC,i} & \text{if } k = 0 \\ -\frac{I(k)}{C_c(k)}\Delta t + V_{SOC}(k) & \text{if } k > 0 \end{cases} \quad (11)$$

$$\forall k \quad V_{t,s}(k+1) = \begin{cases} V_{t,s,i} & \text{if } k = 0 \\ \left(\frac{I(k)}{C_{t,s}(k)} - \frac{V_{t,s}(k)}{R_{t,s}(k)C_{t,s}(k)} \right) \Delta t + V_{t,s}(k) & \text{if } k > 0 \end{cases} \quad (12)$$

$$\forall k \quad V_{t,l}(k+1) = \begin{cases} V_{t,l,i} & \text{if } k = 0 \\ \left(\frac{I(k)}{C_{t,l}(k)} - \frac{V_{t,l}(k)}{R_{t,l}(k)C_{t,l}(k)} \right) \Delta t + V_{t,l}(k) & \text{if } k > 0 \end{cases} \quad (13)$$

$$\forall k \quad V(k) = V_{OC}(k) - I(k)R_s(k) - V_{t,s}(k) - V_{t,l}(k) \quad (14)$$

191 In addition to equality constraints describing the dynamics of the be-
 192 havioral circuit model, equality constraints are used to define the behavioral
 193 circuit parameters C_c , R_{sd} , $C_{t,s}$, $R_{t,s}$, $C_{t,l}$, $R_{t,l}$, R_s , and V_{OC} , which are de-
 194 scribed by empirical functions extracted via experiment, as described in the
 195 literature [24, 26, 27, 28, 29].

196 Finally, the inequality constraints of Equations 15–17 are used to bound
 197 the relevant state variables within limits established by the battery system
 198 operator or battery cell manufacturer.

$$\forall k \quad I_{\text{charge,max}} \leq I(k) \leq I_{\text{discharge,max}} \quad (15)$$

$$\forall k \quad V_{\min} \leq V(k) \leq V_{\max} \quad (16)$$

$$\forall k \quad SOC_{\min} \leq V_{SOC}(k) \leq SOC_{\max} \quad (17)$$

199 The optimization program developed here can be used to manage the
 200 operation of any battery system, provided it has been characterized via ex-
 201 periment, and functions have been developed to describe the empirical circuit
 202 parameters C_c , R_{sd} , $C_{t,s}$, $R_{t,s}$, $C_{t,l}$, $R_{t,l}$, R_s , and V_{OC} . The following section
 203 implements the optimization program for Li-ion energy storage operating in
 204 Texas' restructured electricity to demonstrate the results of the optimization
 205 for a particular battery technology and operational context.

206 4.2. Application to lithium-ion energy storage operating in Texas

207 The Electric Reliability Council of Texas (ERCOT) operates Texas' elec-
 208 tric grid and manages the state's restructured electricity market. Each day,
 209 electricity resources submit information to ERCOT, and then ERCOT exe-
 210 cutes a security-constrained economic dispatch program to minimize overall
 211 electricity costs while maintaining electric reliability [50]. By doing so, ER-
 212 COT clears the market and establishes an electricity price, which can vary
 213 significantly over the day due to variation in electric demand and the avail-
 214 ability of electric generation.

215 Battery energy storage can provide electric energy to ERCOT by per-
 216 forming wholesale energy arbitrage: buying low-cost electricity for later sale
 217 during on-peak hours, when the price for electricity is higher. ERCOT ac-
 218 cepts interconnection requests from electricity generators and storage devices
 219 with a rated power capacity of 10 MW or greater. [51] Even if a storage de-
 220 vice is smaller than 10 MW, it could be aggregated with other small storage
 221 devices by a qualified entity to facilitate its interaction with the ERCOT
 222 market. Storage resources that have been accepted for interconnection to
 223 ERCOT can purchase charging electricity from and sell stored electricity to
 224 the ERCOT electricity market at the corresponding real-time energy price.
 225 It is important for the grid battery operator to manage when their system
 226 charges and discharges in order to maximize the price difference between
 227 charging energy and discharging energy, thereby maximizing operating rev-
 228 enue.

229 We implement the optimization program discussed in the previous section
 230 to manage the operation of a battery system for wholesale energy arbitrage in
 231 ERCOT. Because ERCOT establishes a real-time price for electricity every 15
 232 minutes [50], we consider decision variables for every quarter-hour interval, q ,
 233 of the day. The objective function to be maximized is defined in Equation 18,
 234 where negative values of $P(q)$ denote charging power, positive values of $P(q)$
 235 denote discharging power, and $\pi(q)$ denotes the price for electricity during
 236 price settlement interval q of duration Δt_q .

$$\text{Objective} = \sum_q P(q) \Delta t_q \pi(q) \quad (18)$$

237 We model the dynamics of the battery system at each time step, k , of
 238 duration Δt using the equality constraints of Equations 11–14, with Δt set
 239 equal to 10 seconds. Equation 19 is used to bind the dynamic state variables

240 $I(k)$ and $V(k)$ to the decision variables $P(q)$.

$$\forall q, \forall k \in q \quad P(q) = I(k)V(k) \quad (19)$$

241 The empirical circuit parameters C_c , R_{sd} , $C_{t,s}$, $R_{t,s}$, $C_{t,l}$, $R_{t,l}$, R_s , and V_{OC}
 242 have been extracted from a number of different Li-ion battery cells [24, 26,
 243 27, 28, 29]. To illustrate the operation of our optimization model, we utilize
 244 behavioral parameters extracted from 850-mAh PL-383562 polymer Li-ion
 245 cells by Chen and Rincón-Mora [24]. Li-ion battery energy storage systems
 246 combine a number of series and parallel connected battery cells to meet
 247 the specific power and energy ratings required by an application. Because
 248 the battery cell is the fundamental building block of any Li-ion system, we
 249 consider operational management of a single battery cell to make our analysis
 250 as generally applicable as possible. Different sizes of battery can be modeled
 251 by a summation of individual cell performance. The circuit parameters for
 252 this battery cell are given in Equations 20–26. Within the optimization
 253 program, each of these parameters is described by an equality constraint
 254 imposed at every time step, k . Note that these equations assume negligible
 255 self-discharge and constant-temperature operation at approximately 25°C.
 256 These operating assumptions are acceptable for our purposes, because a grid
 257 battery would not store energy for an extended period of time, and it would
 258 most likely utilize thermal controls to avoid extreme hot or cold operating
 259 temperatures.

$$C_c = 3060 \text{ F} \quad (20)$$

$$V_{OC} = -1.031e^{-35V_{SOC}} + 3.685 + 0.2156V_{SOC} - 0.1178V_{SOC}^2 + 0.3201V_{SOC}^3 \text{ V} \quad (21)$$

$$R_s = 0.1562e^{-24.37V_{SOC}} + 0.07446 \text{ } \Omega \quad (22)$$

$$R_{t,s} = 0.3208e^{-29.14V_{SOC}} + 0.04669 \text{ } \Omega \quad (23)$$

$$C_{t,s} = -752.9e^{-13.51V_{SOC}} + 703.6 \text{ F} \quad (24)$$

$$R_{t,l} = 6.603e^{-155.2V_{SOC}} + 0.04984 \text{ } \Omega \quad (25)$$

$$C_{t,l} = -6056e^{-27.12V_{soc}} + 4475 \text{ F} \quad (26)$$

260 Specifications for a PL-383562 polymer Li-ion battery cell are available
 261 from the manufacturer [52]. We use these specifications to identify values
 262 for the operating parameters that define the inequality constraints of Equa-
 263 tions 15–17. We consider an operating depth of discharge of 80%, assuming
 264 the battery operator would choose to avoid extreme values of state of charge
 265 to extend the lifetime of the battery system. The values considered for each
 266 of the relevant operating parameters are given in Table 1.

267 With the objective function, battery model, and operating constraints
 268 established, we implement the optimization program in the General Alge-
 269 braic Modeling System (GAMS) [53]. We consider an operating period of
 270 24 hours, corresponding to the day-ahead operating timeline of the ERCOT
 271 market [50]. Thus, the optimization program considers 96 decision variables
 272 (the charging or discharging power during each 15-minute price interval, q)
 273 and 8,640 dependent variables (one for each 10-second discretized time step,
 274 k) for each state variable I , V , V_{soc} , $V_{t,s}$, $V_{t,l}$, V_{oc} , $C_{t,s}$, $R_{t,s}$, $C_{t,l}$, $R_{t,l}$,
 275 and R_s . The nonlinear, interior-point optimization algorithm is used to find
 276 optimum values for the decision variables based on the price of electricity,
 277 $\pi(q)$, entered into the program. We utilize Matlab to prepare ERCOT price
 278 data, and then use the GAMS/Matlab link [54] to enter the data to GAMS,
 279 and store the results of the optimization routine.

280 5. Results and discussion

281 To maximize revenue, a battery would provide wholesale energy arbitrage
 282 during an operating day with one or more significant electricity price varia-
 283 tions. Thus, we select prices from August 21, 2011, shown in the top portion
 284 of Figure 2, to illustrate the results of our model. The bottom portion of
 285 Figure 2 shows the corresponding value of the decision variables computed
 286 by our optimization model. The cell power variable is the real electrical
 287 power in W delivered by a single battery cell building block making up a
 288 larger integrated battery system. Positive values of cell power correspond
 289 to discharging, while negative values correspond to charging. The fact that
 290 the values of this variable returned by our algorithm correspond to charging
 291 when the electricity price is low and discharging when the price is high shows
 292 that our algorithm responds appropriately to price fluctuations.

Figure 3 shows the value of dynamic state variables I , V , and V_{SOC} approximated by the battery model encapsulated within the optimization program. The dashed lines indicate the inequality constraints corresponding to the operating parameters listed in Table 1. The results of Figure 3 show that our model can be used to plan the operation of grid battery energy storage within operating limits established by the battery manufacturer or battery system operator. This feature is useful because it may be desirable to avoid certain values of battery voltage, current rate, or state of charge in order to extend the lifetime of a battery system.

To calculate the revenue potential of a battery from its optimal charge-discharge schedule, we solve for the AC power, P_{grid} , flowing between the battery and the grid using Equation 27, and then use Equation 28 to calculate the potential revenue from operating on a given day in ERCOT. We assume an inverter/rectifier efficiency $\eta_{\text{AC-DC}} = \eta_{\text{DC-AC}} = 93\%$ [49, 55].

$$P_{\text{grid}} = \begin{cases} \frac{1}{\eta_{\text{AC-DC}}}P & \text{if charging } (P < 0) \\ \eta_{\text{DC-AC}}P & \text{if discharging } (P > 0) \\ 0 & \text{if idle } (P = 0) \end{cases} \quad (27)$$

$$R_{\text{day}} = \sum_{q=1}^{96} P_{\text{grid}}(q) \Delta t_q \pi(q) \quad (28)$$

A number of normalization methods are used to illustrate the operating revenue of energy storage in a general way. One method is to divide the total operating revenue by the device's rated power to express revenue per unit of power capacity (e.g. \$/kW capacity). A second method is to divide the total operating revenue by the device's rated energy capacity to express revenue per unit of energy storage capacity (e.g. \$/kWh capacity). A third method that is particularly useful for battery systems prone to degradation is to divide the total operating revenue by the total amount of energy *delivered* to the grid (e.g. \$/MWh delivered).

Because a Li-ion battery would degrade with each of its charge-discharge cycles, we use the third normalization procedure described above, and calculate the revenue per MWh of energy delivered to the grid according to Equations 29 and 30. The square brackets in Equation 29 indicate that only discharged energy is counted [56], while the braces in Equation 30 indicate units.

$$E_{\text{delivered}}^{\text{day}} = \sum_{q=1}^{96} P_{\text{grid}}(q) [P_{\text{grid}}(q) > 0] \Delta t_q \quad (29)$$

$$R_{\text{MWh}}^{\text{day}} = \frac{R_{\text{day}} \{ \$/\text{day} \}}{E_{\text{delivered}}^{\text{day}} \{ \text{MWh}/\text{day} \}} \quad (30)$$

322 A battery system dispatched as in Figure 2 would incur an operating
 323 revenue of approximately \$85/MWh delivered calculated according to the
 324 equations above. To understand how the revenue potential of a Li-ion bat-
 325 tery system operating for wholesale energy arbitrage in Texas varies from day
 326 to day, we solve the optimization problem for each day of 2002–2012 using
 327 electricity prices from each of ERCOT’s four hubs: North, Houston, South,
 328 and West. Figure 4 illustrates our results expressed per MWh of electricity
 329 delivered. In each of ERCOT’s four trading hubs, the potential revenue from
 330 energy arbitrage varies significantly from day to day. The greatest revenue
 331 opportunities occurred in 2008, when the average U.S. natural gas price for
 332 electricity generation was high (\$9.26/MMBtu [57]), and in 2011, when a
 333 combination of extreme temperatures and drought caused high electric de-
 334 mand, constrained electric supply, and high summer electricity prices in the
 335 ERCOT region [58].

336 To approximate the expected revenue from the sale of stored energy on
 337 an annual basis, we calculate the revenue per MWh of energy sold annually
 338 according to Equations 31 and 32.

$$E_{\text{delivered}}^{\text{year}} = \sum^{\text{year}} E_{\text{delivered}}^{\text{day}} \quad (31)$$

$$R_{\text{MWh}}^{\text{year}} = \frac{(\sum^{\text{year}} R_{\text{day}}) \{ \$/\text{year} \}}{E_{\text{delivered}}^{\text{year}} \{ \text{MWh}/\text{year} \}} \quad (32)$$

339 Figure 5 shows the average revenue per MWh of energy sold, $R_{\text{MWh}}^{\text{year}}$,
 340 during each operating year, as well as the average revenue per MWh of
 341 energy sold observed over all of the operating years considered. The height
 342 of each bar indicates the average revenue across all ERCOT regions, and the
 343 uncertainty bars indicate the range of revenues observed across all regions
 344 during a given year.

345 To approximate the net-present value (NPV) of Li-ion energy storage
 346 used for wholesale energy arbitrage in ERCOT, we consider values of lifecy-
 347 cle revenue per unit of energy sold, $R_{\text{MWh}}^{\text{lifecycle}}$, ranging from \$7/MWh delivered

348 to \$62/MWh delivered, the minimum and maximum values observed in Fig-
 349 ure 5, respectively. We use \$27/MWh delivered, the average value observed,
 350 as a point estimate. A study by Battke et al. [59] is used to approximate
 351 the cost of Li-ion storage. It reviews multiple recent energy storage cost
 352 studies to develop a cost confidence interval representing the current state of
 353 knowledge among both experts and industry. It approximates the lifecycle
 354 cost of Li-ion capital equipment, maintenance, and degradation (battery cell
 355 replacement), $C_{\text{MWh}}^{\text{lifecycle}}$, ranges from approximately \$250–1000/MWh of elec-
 356 tricity delivered, with a point estimate of \$560/MWh delivered. This figure
 357 allows for a one-to-one comparison between our revenue estimate and the es-
 358 timated cost of a Li-ion battery system. Thus, we calculate NPV by taking a
 359 simple difference between lifecycle revenue per unit of energy sold, $R_{\text{MWh}}^{\text{lifecycle}}$,
 360 and lifecycle cost per unit of energy sold, $C_{\text{MWh}}^{\text{lifecycle}}$. Figure 6 illustrates point
 361 estimates and ranges for revenue, cost, and NPV.

362 As shown in Figure 6, the NPV of Li-ion batteries used in ERCOT for
 363 wholesale energy arbitrage and no other energy storage applications is highly
 364 negative based on our estimate of revenue potential and cost estimates from
 365 the literature [59]. These results indicate that the lifecycle cost of Li-ion
 366 battery energy storage would have to decrease to \$10–100/MWh delivered
 367 for revenue from only wholesale energy arbitrage service in ERCOT to achieve
 368 a positive NPV.

369 It is not surprising that NPV is negative for a Li-ion battery system pro-
 370 viding only wholesale energy arbitrage service. Numerous techno-economic
 371 studies have revealed the fact that most forms of grid energy storage would
 372 have to provide more than one service to the grid to achieve a positive
 373 NPV [35, 42, 38, 49]. In practice, a Li-ion battery system would incur rev-
 374 enue from other grid services, such as ancillary services, in addition to revenue
 375 from wholesale energy arbitrage, the application we consider in detail here.
 376 To understand if there are any occasions when it would be valuable for a
 377 Li-ion battery plant to provide wholesale energy arbitrage to ERCOT, we
 378 examine if there are individual operating days when the potential revenue,
 379 $R_{\text{MWh}}^{\text{day}}$, exceeds levelized storage cost, $C_{\text{MWh}}^{\text{lifecycle}}$.

380 We compare the potential daily operating revenues illustrated in Figure 4
 381 with the lifecycle Li-ion energy storage cost range illustrated in Figure 6.
 382 First, we take the average of the results of Figure 4 across all ERCOT regions,
 383 and sort the result from greatest to least. Then, we plot the sorted data using
 384 a logarithmic scale on the x- and y-axis. Finally, on the same axes, we plot

the lifecycle cost, $C_{\text{MWh}}^{\text{lifecycle}}$, range [59] illustrated in Figure 6. These results are illustrated in Figure 7.

The “value-duration curve” illustrated in Figure 7 is useful because it shows how often revenue from wholesale energy arbitrage service in ERCOT is greater than or equal to the lifecycle cost of a Li-ion battery system leveled per unit of energy discharged. During approximately 7–50 days of the 11-year period studied, the price of electricity is so volatile that it would be possible for revenue from wholesale energy arbitrage to exceed the lifecycle cost per unit of energy discharged. This result suggests that a battery operator should consider the degradation-related cost of performing a grid duty cycle, and how that cost compares with the potential revenue from that cycle, so that a storage device capable of providing multiple grid services can be controlled in an economically efficient way.

6. Conclusion

In this paper, we transformed a behavioral circuit model that has become a popular tool for predicting the dynamic performance of a number of different battery systems [24, 26, 27, 28, 29]. After extracting the differential equations that describe the dynamics of the model’s electric circuit analog, we discretized the model to create an optimization program for economic operational management of a grid battery system. Our optimization program is advantageous because it has the flexibility to manage the operation of any battery system, provided it can be characterized by the model shown in Figure 1. Furthermore, the program can consider any operational context where the decision variable of interest is the instantaneous power flowing to/from the battery system.

In practice, a battery operator could use the methods developed in this paper to control the interaction of their system with the electric grid. First, the battery owner would carry out an experimental procedure to extract the model parameters for their system, as discussed in the literature [24, 26, 27, 28, 29]. Then, the extracted behavioral parameters C_c , R_{sd} , $C_{t,s}$, $R_{t,s}$, $C_{t,l}$, $R_{t,l}$, R_s , and V_{OC} would be entered into our optimization program using equality constraints imposed at each optimization time step, k . Finally, the optimization problem would be solved to plan the operation of the energy storage device to maximize operating revenue without violating the selected operating constraints.

420 To demonstrate the operation of our model, we considered the case of a
421 Li-ion battery system operating for wholesale energy arbitrage in Texas’ re-
422 structured electricity market, which is administered by ERCOT. Our model
423 robustly computed an optimal charge-discharge schedule to maximize daily
424 revenue without violating the battery’s operating constraints during each op-
425 erating day we modeled. Using our results, we found that the NPV of Li-ion
426 energy storage used for only wholesale energy arbitrage in ERCOT would
427 be very negative. However, our results indicate that there are a handful of
428 high-value operating days where operating revenue from wholesale energy ar-
429 bitrage might exceed operating cost. This result suggests that a limitation of
430 our optimization model is that it does not consider the materials-degradation
431 “cost” of providing a battery charge-discharge cycle to the electricity market.

432 In a future publication, we will build upon the model presented here by
433 including the degradation-related cost of charging and discharging within
434 each operational decision considered by the optimization program. By doing
435 so, we hope to show how intelligent operation of a cycle-limited battery device
436 might increase its value. Furthermore, we will augment our operational model
437 to consider the interaction between multiple simultaneous energy storage
438 applications (e.g. wholesale energy arbitrage and ancillary services) and the
439 real-time tradeoff associated with providing one application versus another.
440 By doing so, we hope to reveal a holistic grid battery operation scheme that
441 minimizes battery degradation and maximizes revenue.

442 7. Acknowledgments

443 This work was sponsored by Pecan Street Inc. of Austin, Texas as part
444 of its ongoing smart grid demonstration project, which is part of the Amer-
445 ican Recovery and Reinvestment Act Smart Grid Demonstration Program
446 administered by the U.S. Department of Energy. Special thanks to ERCOT
447 for making their historic electricity price data available to the public.

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Figure 1: The battery lifetime circuit describes the dynamic nature of a battery's state of charge, and the voltage-current characteristics circuit describes how the terminal voltage of a battery is dynamically affected by state of charge and current load. Figure adapted from [24].

Figure 2: The optimization model decides when a battery should charge and discharge to maximize its operating revenue from wholesale energy arbitrage in Texas' ERCOT electricity market. The plots shown here illustrate the optimal charge-discharge schedule on August 21, 2011 in ERCOT's southern hub, with positive values of power indicating discharge.

Figure 3: The optimization model encapsulates an empirical, dynamic battery model to approximate battery state variables during each 10-second optimization time step. This figure shows the dynamic state corresponding to the charge-discharge schedule shown in Figure 2. The dashed lines in each plot indicate the operating parameter limits established in Table 1.

Figure 4: In each of ERCOT's four trading hubs, the potential revenue from energy arbitrage varies significantly from day to day. The greatest revenue opportunities occurred when natural gas prices were high (2008) and electricity resources were scarce (2011).

Figure 5: We calculate the revenue per unit of energy sold during each operating year considered according to Equations 31 and 32. The height of each bar indicates the average revenue across all ERCOT regions, and the uncertainty bars indicate the range of revenues observed across all regions during a given year. The potential revenue varies significantly from one year to another.

*: From [59]. Includes the cost of Li-ion battery capital equipment, maintenance, and degradation. Excludes the cost of purchased charging energy.

Figure 6: The lifecycle cost of storing electricity in Li-ion batteries, $C_{MWh}^{lifecycle}$, is much greater than the potential revenue from wholesale energy arbitrage in ERCOT, $R_{MWh}^{lifecycle}$. This fact causes NPV to be very negative.

Figure 7: Despite the fact that a Li-ion battery used for only wholesale energy arbitrage in ERCOT could not recoup its costs on average, there are approximately 7–50 days during the 11-year period studied when the revenue per MWh of energy discharged exceeds the lifecycle battery system cost per MWh of energy discharged.

Table 1: We establish values for the operating parameters that define the inequality constraints of Equations 15–17 based on specifications provided by the battery cell manufacturer [52].

Operating Parameter	Value
$I_{\text{charge,max}}$	850 mA
$I_{\text{discharge,max}}$	850 mA
V_{min}	3.0 V
V_{max}	4.2 V
SOC_{min}	10%
SOC_{max}	90%