Battery Model for Embedded Systems

Venkat Rao[†], Gaurav Singhal[‡], Anshul Kumar[‡], Nicolas Navet[♠]
[†] Department of Electrical Engineering, Indian Institute of Technology, Delhi
[‡] Department of Computer Science and Engineering, Indian Institute of Technology, Delhi
[♠] LORIA, France
{eeu01174,csu01110,anshul} @cse.iitd.ernet.in, nnavet@loria.fr

Abstract

This paper explores the recovery and rate capacity effect for batteries used in embedded systems. It describes the prominent battery models with their advantages and drawbacks. It then throws new light on the battery recovery behavior, which can help determine optimum discharge profiles and hence result in significant improvement in battery lifetime. Finally it proposes a fast and accurate stochastic model which draws the positives from the earlier models and minimizes the drawbacks. The parameters for this model are determined by a pretest, which takes into account the newfound background into recovery and rate capacity hence resulting in higher accuracy. Simulations conducted suggest close correspondence with experimental results and a maximum error of 2.65% .

1. Introduction

A major constraint in design of mobile embedded systems today is the battery lifetime for a given size and weight of the battery. With the tremendous increase in the computing power of hardware and the relatively slow growth in the energy densities of the battery technologies, estimating the lifetime and energy delivered by the battery has become increasingly important to choose between alternative implementations and architectures for mobile computing platforms.

Currently, designers of mobile computing systems, while using traditional energy optimization approaches like DVS [7] tend to assume that the battery is ideal, that is, it would have a constant voltage throughout the discharge, and would also have a constant capacity for all discharge profiles, which is not always true. It has been documented [6] that the energy delivered by the battery depends heavily on its discharge profile and generally it is not possible to extract the whole of the energy that is stored in the battery. Therefore, it becomes necessary for the process scheduler of a battery operated system to take the discharge profile and battery non-linearities into account, in order to guarantee longer battery life. Such a task demands a fast and accurate battery model that can predict the total energy delivered by the battery depending on the discharge profile.

In early models, the electrochemical processes in the battery have been expressed using partial differential equations [2]. Although they take the recovery effect into account, they are cumbersome and they take prohibitively long (order of days) to estimate battery life [6]. They typically rely on numerical simulation and require significant computation, which makes them impractical. More recently a diffusion based model [9] was also proposed and certain important results for energy efficient DVS were formally proved. Although the model itself is very comprehensive it still is computation intensive and might not be feasible for real-time applications.

Stochastic battery models [6, 8] have also been proposed which are faster than to the PDE model and also inculcate the recovery and rate capacity effects but we have found that these were not sufficiently sensitive to predict certain experimental observations dealing with recovery.

The goal of this paper to provide a fast and accurate battery model. The rest of the paper is organized as follows. Section 2 discusses the basic phenonmenon that effect battery life. Section 3 takes a look at the relevant battery models, their strengths and drawbacks. Section 4 explains the experimental setup and the results which were inexplicable by the existing models, motivating the need for a new battery model. The proposed battery model is described in section 5. In section 6, we describe the simulations based on the model and show that the model explains the experiments accurately. Section 7 concludes the paper and explores future research.

2. Battery Basics

A battery cell is characterized by the open-circuit potential (V_{OC}), i.e. the initial potential of a fully charged cell

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under no-load conditions, and the cut-off potential (V_{cut}) at which the cell is considered discharged. Each cell consists of an anode, a cathode and the electrolyte that separates the two electrodes. The electrical current obtained from a cell results from electrochemical reactions occurring at the electrode-electrolyte interface [4]. The two important effects that make battery performance sensitive to the discharge profile are (i) Rate Capacity effect, and (ii) Recovery effect.

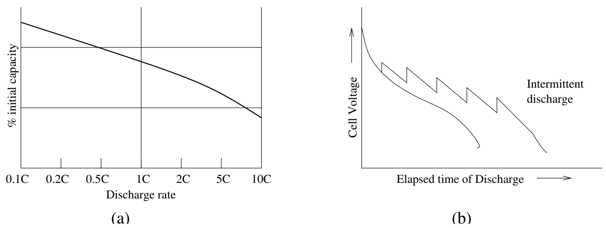

Figure 1. **Non-ideal battery properties: (a) Rate Capacity effect, (b) Recovery effect (Figure taken from [5])**

The lifetime of a cell depends on the availability and reachability of active reaction sites in the cathode. When discharge current is low, the inactive sites (made inactive by previous cathode reactions) are distributed uniformly throughout the cathode. But, at higher discharge current, reductions occur at the outer surface of the cathode making the inner active sites inaccessible. Hence, the energy delivered (or the battery lifetime) decreases since many active sites in the cathode remain un-utilized when the battery is declared discharged. Concentration of the active species (charged ions of Lithium and Nickel) is uniform at electrode-electrolyte interface at zero current. As the intensity of the current is increased, the deviation of the concentration from the average becomes more significant and the state of charge as well as the cell voltage decrease. This phenomenon is called *Rate Capacity effect* [1]. Figure $1(a)$ shows the loss of capacity with increasing load current for a typical NiCd battery [4]. The C rating is specified as the capacity for a given time of discharge.

Some of the adverse consequences of constant current discharge can be overcome when the discharge is pulsed. If a cell is allowed to relax long enough after delivering a pulse, the diffusion process compensat:es for the depletion of the active materials that takes place during the current drain. The degree to which the battery recovers depends on the discharge profile (rate) and the length and distribution of the idle slots, as well as the details of the battery construction. This non-linearity in the battery, has been termed the *Recovery effect* [5] and is shown in Figure $1(b)$.

These facts suggest that the discharge process may be a significant determinant of the delivered energy. In order to investigate this possibility systematically, we need models for representing the battery behaviour.

3. Relevant Battery Models

3.1. Kinetic Battery Model (KiBaM)

The Kinetic Battery Model(KiBaM) [3] models the battery as two wells of charge, as shown in Figure 2. The available-charge well supplies electrons directly to the load, the bound-charge well supplies electrons only to the available-charge well. The rate of charge flow between the two wells is set by k and the difference in the heights of the two wells, h_1 and h_2. The state of charge of the battery is h_1, i.e. when h_1 is unity the battery is fully charged and when it is zero the battery is fully discharged. The internal resistance of the battery is represented by R_0. Parameter c is a capacity ratio and corresponds to the fraction of total charge in the battery that is readily available.

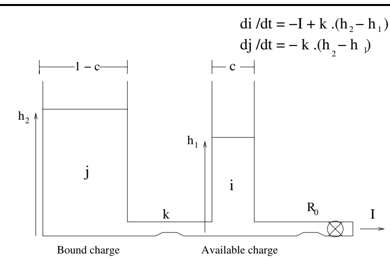

Figure 2. **Kinetic Battery Model, models battery as two wells of charge - available and bound**

Taking an example, a load I is drawn from the battery. The available-charge well would be reduced rapidly, and the difference in h_1 and h_2 would become large. Now when the load I is removed, charge would flow from the bound-charge well to the available-charge well until h_1 and h_2 become equal again. The battery's open-circuit voltage would increase, and now more charge would be available to the load than it would have been if it had been connected throughout to the load until h_1 went to zero. KiBaM is useful in getting an intuitive idea of how and why the recovery occurs but it needs a number of additions to be useful for the types of batteries used in mobile computing.

3.2. Stochastic Battery model

The stochastic model [6] focuses on the Recovery effect and models the battery behavior as a Markov process with probabilities in terms of parameters that can be related

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to the physical characteristics of an electro-chemical cell. A fully charged cell is assumed to have a maximum available capacity of T charge units, and a nominal capacity of N charge units, where a charge unit defines the granularity of charge transfer. The nominal capacity, N, is much less than T in practice and represents the charge that could be extracted using a constant discharge profile. Both N and T vary for different kinds of cells and values of discharge current.

The process starts from the state of full charge ($V = V_{OC}$), denoted by N, and terminates when the absorbing state 0 ($V = V_{cut}$) is reached, or the maximum available capacity T is exhausted. By allowing idle periods in between discharges, the battery can partially recover its charge , and thus we can drain a number of charge units greater than N before reaching the state 0.

The model is fast and reasonably accurate but was found to be not sensitive enough to predict the experimental observations (Section 4).

4. Experimental Setup

We conducted experiments using a simple setup (Figure 3) to observe and explore the recovery effect in batteries. A 1.2 Volts AAA Ni-MH battery was connected in series with a Power Supply. A simple inverter configuration using npn transistor (SL100) was used to discharge the battery. A power supply was connected in series with the battery because 1.2 Volts were not enough to drive the transistor into saturation. Square waves of different frequencies using a function generator were given at the base of the transistor, which resulted in pulsed discharge from the battery. The resisitance R_c was set so that current drawn is 960 mA from the battery plus power supply connected in series.

It was observed (see Table 1) in Experiment Set 1 that the energy delivered by the battery was different for different frequencies even though the duty cycle was kept 50% for all the experiments. This result was inexplicable with the existing models as according to them energy delivered should have been the same because 50% duty cycle implies equal duration of idle time, and hence equal recovery. These observations proved the dependence of charge recovered on the distribution of idle time.

Frequency (Hz)	**Time to discharge** (min)	**Charge Delivered** (mAh)
Continuous	90	1440
1000	182	1456
1	193	1544
0.2	230	1840

Table 1. Results from Experiment Set 1

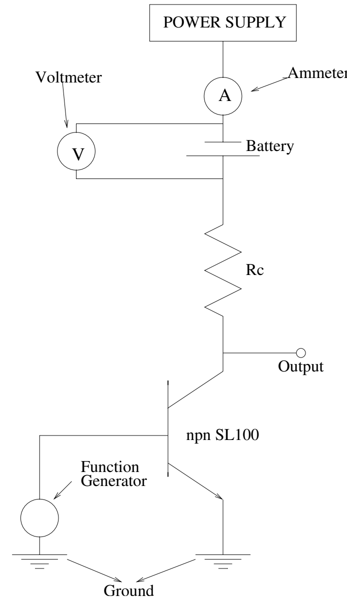

Figure 3. Circuit to test Battery Recovery

We conducted a new set of experiments(Experiment Set2) to further explore how recovery varies within a single idle slot. We used the same setup but the duty cycle and frequencies of the square waves were varied so as to achieve constant ON time and variable OFF time(length of idle slot). The results are presented in the Table 2.

ON (sec)	**OFF** (sec)	**Discharge time** (min)	**Charge Delivered** (mAh)
2	0	90	1440
2	0.5	114	1459.2
2	0.75	130	1512.7
2	1	151	1610.7
2	2	228	1824
2	2.5	259	1841.8
2	3.5	317	1844.4

Table 2. Results from Experiment Set 2

5. Stochastic Modified KiBaM

We model battery discharge as 3-dimensional Markov process which is a stochastic extension of the Kinetic Battery model with certain refinements and additional parameters for accuracy. The modified Kinetic Battery model is as follows, Battery is modeled as two wells of charge, as shown in Figure 4. The available-charge well supplies electrons directly to the load, the bound-charge well supplies

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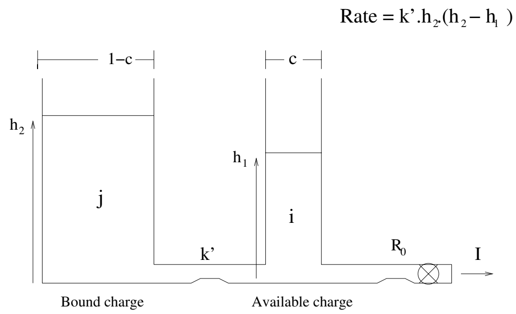

Figure 4. **Modified KiBaM with rate of transfer between two wells is equal to** $k'.h_2.(h_2 - h_1)$

electrons only to the available-charge well. Parameter c is a capacity ratio and corresponds to the fraction of total charge in the battery that is readily available. Parameter i represents the amount of charge in the available charge well and j represents charge in bounded charge well at any point during the battery life time. The rate of charge flow between the two wells is a function of k', height h_2 and the difference in the heights of the two wells, h_1 and h_2. The dependence on height h_2 reflects the observation that a battery has more tendency to recover when it has more charge left. The internal resistance of the battery is represented by R_0. Without loss of generality, the wells can be considered as two dimensional which results in the following equations

$$\begin{array}{l} h_2.(1-c) = j \\ h_1.c = i \end{array} \qquad (1)$$

The battery is modeled using three state parameters (i, j, t), making a three dimensional Markov chain structure. Parameters i and j as explained above are the amount of charge stored in available and bound well of charge respectively, t is length of the current idle slot i.e. time since some current was drawn from the battery previous to the current moment. Parameters i and j are measured in charge units, where a charge unit is the smallest unit of charge that can be drawn from the battery or depends upon the granularity of the simulation and t is measured in time units, where a time unit is the least count of the time in simulation.

Battery behaviour is represented as a discrete time transient Markov process, that keeps tracks of the three parameters of the battery. The battery discharge starts from the state of full charge i.e. with initial of values of parameters i and j (subject to the battery used) and $t = 0$, and terminates when the battery is discharged, i.e. being in any of states having $i = 0$. q_I is the probability that in one time unit, called a time slot, **I** charge units are demanded. This is modeled as I charge units per unit time are drawn from the available charge well while some charge **J**[Eq.(2)] is being transferred or replenished by the bounded charge well, to the available charge well.

$$\begin{array}{l} (i, j, 0) \longrightarrow (i - I + J, j - J, 0) \\ J = k'.h_2.(h_2 - h_1) \end{array} \qquad (2)$$

If there are idle periods in between discharges, the battery can partially recover its charge during these idle times,and thus we can drain a larger number of charge units before reaching the states having parameter $i = 0$ i.e. fully discharged states. Let the probability that an idle slot occurs be q_0.

If the given idle slot is infinitely long, there will occur adequate transfer of charge from the bound well to the available well so as to equalize the heights. However, this recovery or transfer of charge is not constant over the idle slot, but varies with the length of the idle slot. This variation in the recovery of charge over time in an idle slot is a characteristic of the battery used and can be obtained by analysing results of Experiment Set 2 as described later.

An approximated best fit curve will represent the average recovery per idle slot and serve as a characteristic for the particular battery. The differential(**p(t)**) of the curve gives the probability to recover with time during an idle slot. During a given idle slot the battery may or may not recover. The quanta(**Q**) of charge it recovers depends on the current state of the battery i.e. height h_2 , $(h_2 - h_1)$ and the granularity of time. The quanta(**Q**) of recovery is calculated so as the charge recovered for an infinitely long idle slot is equal to total charge that needs to be transferred between the two wells before there heights are equalized. If there is no recovery then there will be no change in the values of parameter i and j while t is incremented by one for the next successive idle slot. Figure 5 shows the possible transitions during an idle slot. Equations 3 and 4 summarizes the transitions and their probabilities respectively.

$$(i, j, t) \quad \longrightarrow \quad \begin{cases} (i + Q, j - Q, t + 1) & (i) \\ (i, j, t + 1) & (ii) \\ (i - I + J, j - J, 0) & (iii) \end{cases} \qquad (3)$$

The probability for transition (i) and (ii) respectively are

$$\begin{array}{l} p_r(i, j, t) = q_0.p(t) \\ p_{nr}(i, j, t) = q_0.(1 - p(t)) \end{array} \qquad (4)$$

The probability for transition (iii) is q_I.

The rate capacity effect is automatically incorporated in the model, because as the discharge current increases, charge in the available well decreases more rapidly giving the bound charge well less time to replenish the available charge well and battery is declared to be discharged even though there is a lot of charge left inside the bound charge

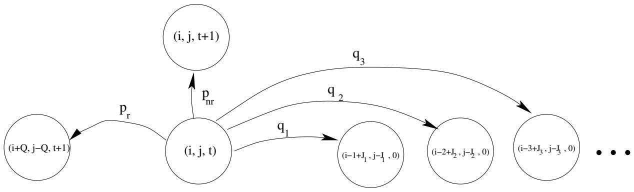

Figure 5. **Transition probabilities**

well, resulting in the inefficiency known as rate capacity effect.

The Model can be easily extended to calculate battery life for deterministic discharge profiles. At each step of the simulation, we look at the input discharge waveform and calculate the average current over each time slot, converting it into appropriate number of charge units depending on the time unit of the simulation. The number of charge units(I) calculated are drawn from the battery model with $q_I = 1$, while recovery during an idle slot still remains probabilistic.

6. Simulations

In this section, we use our proposed stochastic battery model to predict the battery life and delivered energy by the battery and compared it with the actual experimental values.

The parameter k' and the initial values of i and j are the characteristics of the battery which is being discharged. The maximum capacity of the battery is defined as the charge delivered by it under infinitesimal load. Similarly the charge in the available well is defined as the charge that would be delivered if we were to draw infinite current. We can evaluate these values by plotting a load Vs delivered capacity curve for the battery and extrapolating the ends (see Figure 6). The battery used in our experiments has a maximum capacity of 2000 mAh. Also the simulation least count in time was chosen to be 10 ms.

The charge in the available well, when the battery is fully charged is taken as 1250 mAh i.e. 45,00,00,000 charge units (1250 mAh = 1250*3600*100 mA-10ms). The remaining charge present in the bound well is 750 mAh i.e. 27,00,00,000 charge units. These initial values of charge in the two wells gives us the value of parameter $c = 0.625$ by ensuring that the height of the two wells is same.

Also the behaviour of the battery under an idle slot can be determined by a pretest on the lines of Experiment 2. The total charge recovered was calculated for each of the observations of experiment 2 with constant current discharge at 960 mA as the reference. All the profiles were periodic and therefore average recovery per idle slot can be approximated as total recovery divided by the number of idle slots

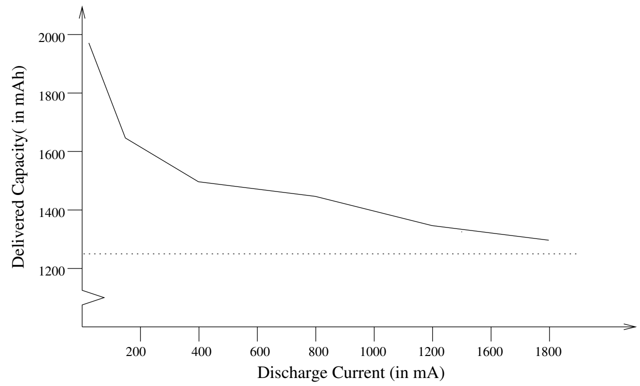

Figure 6. **Delivered Capacity Vs Constant Discharge Current**

occuring during the life time of the battery. This average charge recovery per idle slot represents battery behaviour during idle periods.

The diifferential of this curve gives us the probability to recover in an idle slot with time, which governs the amount of recovery during an idle slot.

For each of the experiments the ON current drawn is $I_{ON} = 960$ mA and $I_{OFF} = 0$ mA when there is an idle slot.

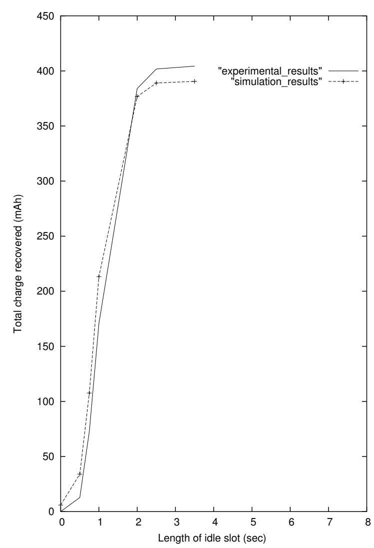

Figure 7. **Simualtion results**

A C simulation of our model were run several times on a P4 Desktop with 256MB RAM using the above mentioned parameters, and the results were averaged to approximate battery lifetime and charge delivered by the battery. Simu-

Frequency (Hz)	Predicted Discharge time (min)	Experimental Discharge time (min)	Predicted Charge Delivered (mAh)	Experimental Charge Delivered (mAh)	% Error ()	Run Time (msec)
Continuous	90.2	90	1445.8	1440	0.4	1621
1000	180.8	182	1446	1456	- 0.69	2856
1	192.6	193	1540	1544	- 0.26	2953
0.2	226	230	1807	1840	- 1.8	3152

Table 3. Simulation results for Exp. Set 1

ON (sec)	OFF (sec)	Predicted Discharge time (min)	Experimental Discharge time (min)	Predicted Charge Delivered (mAh)	Experimental Charge Delivered (mAh)	% Error ()	Run Time (msec)
2	0	90.2	90	1445.8	1440	0.4	1621
2	0.5	115.2	113.5	1474.5	1459.2	1.39	2154
2	0.75	133	130	1547.6	1512.7	2.28	2359
2	1	155	151	1653.3	1610.7	2.65	2607
2	2	227	228	1816.7	1824	- 0.4	2915
2	2.5	257.5	259	1829	1841.8	- 0.7	3354
2	3.5	314.6	317	1830.5	1844.4	- 0.76	4234

Table 4. Simulation results for Exp. Set 2

lation results for Experiment Set 1 are presented in Table 3. For Experiment Set 2, simulation results are summarized in the Table 4 and Figure 7. Simulation results suggest that the model was quite accurate in predicting the battery life and charge drawn for the battery with a maximum error of 2.65%.

7. Conclusion and Future work

Energy-autonomous embedded systems have an attached finite-capacity energy source - a battery, that must be relatively small and light for the embedded system to be mobile. Consequently, the system energy budget is severely limited, and efficient energy utilization becomes one of the key problems in the context of battery-powered embedded computing. In this paper we have presented a stochastic battery model and a framework for estimating the battery life as well as the delivered energy for embedded systems powered by battery. The proposed model is fast and accurate as shown by the simulations. In future we would like to conduct experiments on different battery technologies, to have a better picture of the behaviour of battery in general. The battery model in conjunction with voltage scaling can be used for designing algorithms for battery aware task scheduling on Real-time mobile embedded systems.

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