MACROMODELING OF BATTERY DISCHARGE AND RECOVERY FOR MOBILE EMBEDDED SYSTEMS‡

Ying Zhang* and Krishnendu Chakrabarty
Dept. of Electrical & Computer Engineering, Duke University
Durham, NC 27708, USA
{yingzh, krish}@ee.duke.edu

Battery power management is a key enabling technology that is responsive to a number of needs outlined in the *Concepts for the Objective Force*. Power management prolongs battery life and reduces logistic footprint replenishment demand, leading to systems that are *sustainable*. Power management also leads to lightweight systems that are easily *deployable*.

Power management is especially important for embedded systems, which cannot be physically accessed, such as concealed sensors that are deployed in the field for surveillance, force protection, and search and rescue missions. Battery lifetime is therefore a key consideration for such systems. It is also an important measure of system performance. If only a single battery is available, battery life can be prolonged using low-power hardware design and software-driven dynamic power management. A drawback of these techniques however is that they assume the battery subsystem to be an ideal source of energy, which implies that the battery output voltage remains constant during the discharge period and drops abruptly to zero when the battery is fully discharged. However, in reality the output voltage decreases with time, and when the output voltage falls below a pre-determined threshold (usually 80% of the nominal voltage), the battery is considered exhausted. The total discharge time is defined as the battery lifetime.

Battery discharge can be of two types. The first is termed continuous discharge, which implies that energy is drawn from the battery continuously without any relaxation (period of rest). The second type of discharge is termed intermittent discharge, which implies that the battery goes through periods of rest between successive discharges. The periods of rest allow the battery to recover some of its deliverable charge. This property, described as a recovery effect, can be explained using electrochemical analysis.

While it is common for battery vendors to provide discharge profile information, closed-form mathematical formulas for the output voltage are typically not provided. Furthermore, no recovery profiles are available for any of the commercial batteries. We therefore pose the following question: how significant is the recovery effect for these batteries? If the recovery effect is not significant, then we can ignore it for power management and concentrate exclusively on the discharge profile. On the other hand, if the recovery effect is significant, it must be taken into account for power management. This question is comprehensively examined in our work by experiments.

Multiple-battery systems offer a number of interesting possibilities. One option in such cases is to use a second battery only after the first battery is drained. The total battery lifetime is in this case simply the sum of the lifetimes of the two batteries. A more attractive option is to exploit the fact that most batteries can recover some of their lost charge during periods of relaxation. It is however seldom utilized by embedded system power management techniques. Our objective here is not to add to the body of knowledge in electrochemical analysis, but to leverage this property to prolong battery lifetime for an embedded system.

The recovery effect in batteries opens up the possibility of battery scheduling in multiple-battery systems. The main idea here is to use multiple batteries in an interleaved fashion so as to prolong the combined battery life. The first challenge in battery switching however is to develop high-level macromodels for battery discharge and recovery. These models should ideally provide an analytical characterization of discharge and recovery as functions of time and battery load.

The physical properties of interest in a battery are output voltage and battery capacity. Recent research on battery modeling has focused either on low-level microscopic effects, or attempted high-level modeling using stochastic methods. For the low-level modeling, the battery electrochemical process is expressed using partial differential equations. Although they take recovery effect into account, they are cumbersome. They typically rely on numerical simulation and require significant computation, which makes them impractical for system-level power management. For the high-level modeling, some describes battery behavior as a discrete Markov process. The effectiveness, however, appears to be limited to specific types of applications. A number of

‡ This research was supported in part by DARPA and Army Research Office under Award No. DAAD19-01-1-0504. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the view of the DARPA and ARO agencies.

alternative high-level battery models have recently been proposed using VHDL or PSPICE. The major drawback of these models is that they do not consider the recovery effect. As a result, their predictions cannot be used to prolong battery life through the use of battery scheduling.

In this work, we postulate analytical high-level models to characterize the battery output voltage as a function of time for constant load conditions. The models are composed of two separate parts on discharge and recovery. The models are parameterized by the size of the battery load. These models represent a first step towards comprehensive battery modeling, and their simplicity is expected to facilitate battery scheduling for mobile embedded systems. To the best of our knowledge, this is the first attempt to develop and validate high-level models that take into account the system workload, and both the discharge and recovery profiles.

The macromodels are validated using a simple laboratory setup and three representative batteries chosen from alkaline, nickel-metal-hydride (NiMH), and lithium-ion respectively. It is shown that the proposed macromodels are a close fit with actual battery behavior. We also investigate the magnitude of the recovery strength in each case to determine if it is worthwhile to consider battery recovery for system-level power management. It is demonstrated that the recovery effect is significant and it should be exploited for prolonging battery lifetime. Moreover, we compare the behaviors between continuous discharge profile and intermittent discharge profile. A striking observation is that the discharge becomes more aggressive after recovery in the intermittent discharge process. As a result, the effect of relaxation becomes two-fold. First, the battery undoubtedly recovers some capacity, which increases lifetime. Second, an idle period in some sense resets the next discharge cycle. After the idle cycle, the battery discharges at almost the same rate as at the start of the previous discharge cycle. On the other hand, in continuous discharge, the battery discharge rate decreases progressively. The “discharge rate reset” phenomenon has a negative impact on battery lifetime. To prolong system lifetime, the two-fold impact must be carefully examined to determine under what conditions the battery lifetime is enhanced most.

Based on our proposed models, we further estimate the lifetime of dual-battery system under intermittent discharge profile. Recovery effect is incorporated as a key factor. A mathematical expression of system lifetime is obtained. The result can be applied to calculate optimal interval length for discharge and recovery to maximize the system lifetime.

Figure 1 illustrates the experimental discharge profile for load resistance 18.3Ω for SCH8500 battery. The discharge profile predicted by the macromodel is also shown. We observe that when the output voltage is greater than the battery’s nominal voltage V_n, the battery is discharged at a rate that matches the analytical model extremely well. The analytical model breaks down when the output drops below V_n; from this point onwards, the battery voltage drops precipitously with time. However, since a battery is considered useful only for output voltages greater than the threshold, the analytical model serves as an effective predictor of battery voltage.

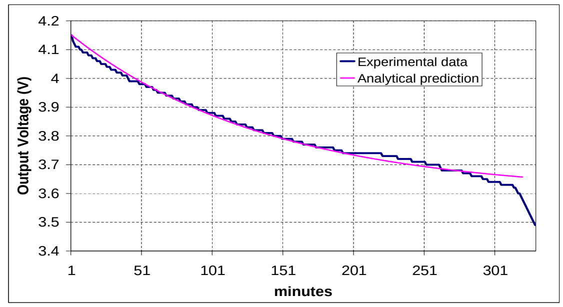

Figure 1: Continuous discharge profile.

Figure 2 illustrates the recovery effect for the Samsung SCH8500 Li-ion battery. We obtained a close fit with the experimental data; the postulated recovery model matches the experimental results very well.

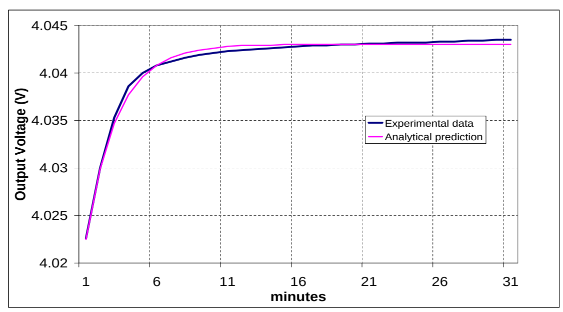

Figure 2: Recovery profile.

We obtained a similar close match between analytical predictions and experimental results for intermittent battery discharge, in which periods of discharge are interleaved with periods of recovery.

In summary, we have postulated analytical high-level models to characterize the battery output voltage. We have validated our analytical models through laboratory experiments based on the alkaline, nickel-metal-hydride (NiMH), and lithium-ion batteries. These models represent a first step towards comprehensive battery modeling, and their simplicity is expected to facilitate battery scheduling for mobile embedded systems. We have demonstrated that the recovery effect is significant for the alkaline and the NiMH batteries, and the recovery magnitude is comparable to the discharge magnitude.