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A Method for Estimating State of Charge in Energy-Aware Wireless Sensor Nodes

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Abstract. – The estimation of the Lithium-Ion battery State of Charge in a sensor node represents a challenging problem. The methods currently proposed in literature are mainly devoted to characterized the state of charge in portable electronic devices; however, their implementation in sensor nodes results to be unfeasible, both for the energy consumption and for the computational complexity. In this paper we will present a method for estimating the battery State of Charge, mainly based on a virtual implementation of the Coulomb Counting method, that aims to overcome some of the drawbacks of the existing methods and to fulfill the more stringent requirements presented by a sensor node.[1]

I. Introduction

Wireless sensor networks are typically used in applications where wired infrastructure is avoided. Therefore, each sensor node needs its own energy supply unit. Sustainable WSNs are powered by energy harvesting systems, which harvest and buffer the energy from the environment into rechargeable batteries. A primary concern in the design of network nodes consists of designing efficient management policies able to minimize the power dissipation and extend battery runtime. The implementation of these policies requires the knowledge of the available energy stored into a battery which is strictly related by the battery State of Charge (SoC) .

Obtaining an accurate estimate of this quantity however is not a trivial task. In literature different methods have been proposed for making portable electronic devices, such as laptops, personal data assistants, cellular phones, shavers and so on, conscious of their energy status [1], [2], [3].

The simplest method consists in measuring the voltage drop across battery terminals under the assumption that no current will be absorbed by the load during the measurement. Under the hypothesis that the relationship between the SoC and the open circuit battery voltage is known, the former can be easily obtained. The aforementioned relationship can be determined by experimental measurements providing the state of charge respect with the battery electromotive force or by using data provided by the battery constructor [4]. In this latter case the resulting accuracy is lower. This method presents some severe limitations. One of these is to satisfy the hypothesis of measuring the open circuit voltage. In the case of sensor nodes this assumption cannot be completely fulfilled since the measurement system itself absorbs current to work. Furthermore, while the voltage based method for estimating the SoC provides reasonably meaning results for a lead-acid battery, in the case of lithium-ion batteries this method is not feasible. The discharge curve of the battery in fact presents a very low sensitivity with respect to the state of charge; moreover it strongly depends on temperature. The sensitivity however slightly increases when the battery is almost fully discharged and when the battery is almost completely charged. Therefore, the voltage-based method can be used for providing a full charge or a low charge indication about the energy status of a battery.

Another method proposed in literature is based on Coulomb counting [5]. This method involves the measure of the discharging current flowing out of the battery and the integration of this current in time. The discharging current is estimated by measuring the voltage drop over a shunt resistance of known value. Accurate estimates of the battery state of charge can be obtained. It however requires a relatively high power consumption since current needs to be continuously sampled.

A battery state of charge estimation procedure specifically designed to be executed on a sensor node has been proposed in [6]. This is based on a battery state of charge tracking method, performed using a counter that tracks the battery consumption and recharge. The energy consumption is accounted by incrementing the counter value at each program cycle, while whenever the battery results to be fully charged the counter is reset to zero. An upper bound on the counter value is used to identify a low battery state. This method presents some drawbacks, for instance it cannot be used to track the state of charge in sensor nodes that make use of interrupt service routines and furthermore, the state of charge can be known only at the beginning or at the end of a program cycle, but not in the middle.

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The method presented in this paper is appositely developed for a sensor node. It aims to overcome some of the drawbacks of the existing methods and to fulfil the more stringent requirements presented by a wireless sensor node. It is mainly based on a virtual implementation of the Coulomb counting method, founded on the assumption that a sensor node presents a highly predictable behaviour that can be accurately described by a finite state machine. This makes possible to determine *a-priori*, by laboratory measurements, the discharge current for the different tasks executed from the sensor node. These values will be stored in the memory of the microcontroller and used to determine the battery state of charge. The results presented in this paper have been obtained by implementing the proposed measurement system in a sensor node of the XLP 16-bit development kit bought from Microchip Technologies having an EnerChip^{TM} EH CBC5300 Harvesting Module as power source.

II. Lithium-ion battery parameters

A rechargeable Lithium-Ion (Li-Ion) battery can be simply viewed as a transducer capable of converting chemical energy into electrical energy and vice versa, where this conversion occurs through electrochemical reduction-oxidation reactions. Due to the difficult of working directly with electrochemical relationships, several synthetic parameters are introduced, by which accurately describe the behaviour of a battery during its life time.
The most important is the *discharge characteristic*, which provides the relationship between the open circuit voltage $V_{battery}$ across battery terminals and its state of charge SoC, that corresponds to the percentage of a maximum possible charge that is present inside the battery.
In Fig. 1 an example of Li-Ion battery transcharacteristic is reported. This curve has been obtained by the analytical model provided in [7] and it provides a typical behaviour. The open circuit voltage $V_{battery}$ is a non-linear monotonically decreasing function of the state of charge which depends on both temperature and discharging rate. However, within a given error tolerance, the discharge function can be simplified to be independent of these variables.

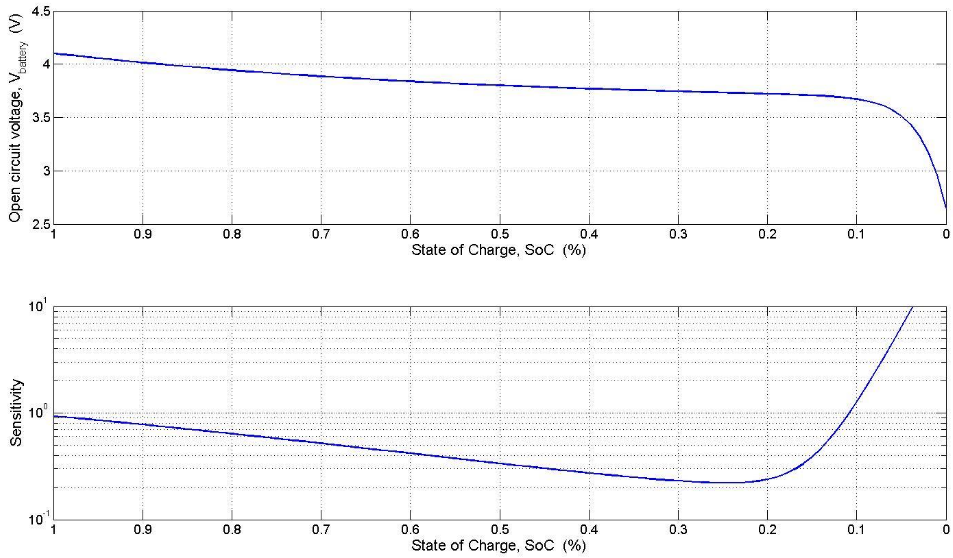

Fig. 1: Typical discharge curve and sensitivity for a Li-Ion battery at room temperature. This curve has been obtained by using the analytical model provided in [7] that provides the open circuit voltage when the state of charge is known:
$V_{battery} = -1.031 \cdot e^{-35 \cdot SoC} + 3.685 + 0.2156 \cdot SoC - 0.1178 \cdot SoC^2 + 0.3201 \cdot SoC^3$.

By considering the sensitivity, the transcharacteristic of a battery can be divided in three zones, called H, M and L[2]. The region H refers to an almost fully charged battery where the SoC is greater than a given threshold, typically between 70% and 80%. In this region the sensitivity is enough (>0.5) for estimating the SoC directly by the inverse transcharacteristic $SoC = f^{-1}(V_{battery})$ where $V_{battery}$ corresponds to the voltage drop measured across battery terminals, and successively. In the region M the sensitivity gets lower and $V_{battery}$ depends in a negligible way from the state of charge. In this case, accurate estimates of the SoC cannot be obtained by a direct measure of $V_{battery}$ and different methods need to be taken into account. Finally, the third

[2] H, M and L mean respectively an high, medium and low charge state.

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region, indicated by L, corresponds to a very low charge state. In order to preserve the cycle life and other performances of the battery, it is important to terminate the battery discharge when the battery reaches this state. If the discharge process continues the battery will be irreversibly damaged.
Another important parameter that must be considered when an estimate of the state of charge is performed is the internal resistance of battery, also called *inertial resistance*. This resistance is affected by the temperature T, and by the battery state of charge. If I is the current provided by the battery, the open circuit voltage can be calculated using the following equation:

$$V_{battery} = V_{meas} + I \cdot R_{battery} \tag{2}$$

where V_{meas} is the voltage measured across the battery terminals. We can note that $V_{battery} = V_{meas}$ only if $I = 0$, that means that no current is absorbed by the load during the measurement. This assumption cannot be fulfilled in a sensor node, since the measurement system itself absorbs current to work and it is not possible to use a secondary energy source to feed up the SoC measurement system as in the case of portable electronic devices. Therefore, the voltage drop $I \cdot R_{battery}$ will be evaluated by laboratory tests and successively compensated.

III. Proposed method

The method proposed in this paper, complies with the strict energy constraints that are required for the sensor node. In particular, the most significative features of the method regard a specific set of design choices, which aims to reach simplicity, accuracy and reliability in relation to the energy consumption.
In the present discussion the operating cycle of the sensor node is modelled as a finite state machine. The sensor node operates into two macro states: the *sleep state* is referred to the sensor's operating mode in which the energy consumption is kept low by straitening the main actions. The *active state* corresponds to the activity mode in which the sensor node performs all the designed actions.
The measurement routine is executed while the sensor node is in the *active state*. It operates in two phases: the first aims to determine the battery state by considering the discharge characteristic, while the second provides a state of charge estimate.
At the beginning, $V_{battery}$ is calculated from V_{meas} by compensating the voltage drop. The battery state is then determined by comparing $V_{battery}$ with two suitable thresholds obtained from V_{TH}, that represents the voltage correspondent to the state of charge of about 50%: $V_{TH} + \Delta_1$ and $V_{TH} - \Delta_2$. Δ_1 and Δ_2 are properly calculated; in particular, they must be higher than the resolution of the analog-to-digital converter.
The region H is entered when $V_{out} > V_{TH} + \Delta_1$, here a charge level estimate can be directly achieved starting from the voltage measure:

$$SoC_H = f^{-1}(V_{battery}) = a \cdot V_{battery} + b \tag{3}$$

where a and b are respectively the slope and the offset of the straight line that approximates the inverse function of the discharge profile in the region H.
In the region M, where $V_{TH} - \Delta_2 < V_{out} < V_{TH} + \Delta_1$, a Coulomb counting strategy is adopted. The Coulomb counting method consists in measuring the current flowing out of a battery and in integrating this current over time to determine the capacity variation:

$$Q(t) = Q_0 - \int_{t_0}^{t} i(\tau) d\tau \tag{4}$$

where $Q(t)$ is the battery capacity at the time instant t and Q_0 is the initial capacity at the time instant $t = 0$. The state of charge can be obtained from Eq. (1), by setting $Q_{atual} = Q(t)$. In the case of a sensor node, the current $i(t)$ is characterized by a succession of bursts associated to the execution of well-defined tasks (see Fig. 3). In general, this behaviour is strictly related to the energy consumed in a sensor node. This can be distinguished between static power, required when the node is in sleep or deep sleep mode and dynamic power, required from the node when it operates in the active or idle state. This latter contribution can be divided into the energy consumed by the microcontroller and the energy required by the peripheral modules (sensing block and communication block) to work. Under the assumption of partitioning the temporal axis in adjacent intervals, where each interval refers to the execution of a given task, we obtain:

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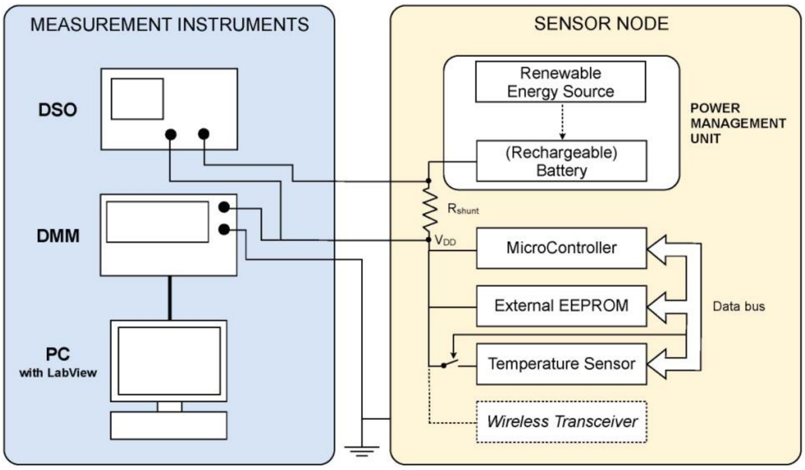

Figure 2. Measurement setup

$$SoC = SoC_H - \sum_i N_{task,i} \cdot \frac{Q_{task,i}}{Q_{battery}} \cdot 100 \quad (5)$$

where $Q_{task,i}$ is the charge provided by the battery for the execution of the i-th task, $N_{task,i}$ is the number of executions of the i-th task in region M. $N_{task,i}$ is reset when the battery enters the region H. Finally, $Q_{battery}$ represents the usable capacity and it must be carefully initialized.
Lastly, in the third region L the sensor node must suspend all the operations to prevent battery damages.

IV. Experimental Results

A. Measurement setup

The measurement set-up is reported in Fig. 2. It consists of a Digital Storage Oscilloscope (DSO) Tektronix TDS5032B and a 6 ½ digits Digital Multimeter (DMM) HP 34401A connected by a GPIB interface to a personal computer (PC) running LabView. The sensor node communicates to the PC throught a serial interface (UART); it allows to verify the correctness of operations of the firmware in relation with the discharge profile measured with the multimeter. The sensor node used in this example is composed of a power management unit (PMU) which provides the power to the board and the board itself. The PMU is composed of a renewable energy source which charges the battery and two rechargeable batteries EnerChip CBC050. The board consists of a MicroController (μC) unit connected by an I^2C bus to an external EEPROM and a temperature sensor. The firmware that provides the functionality of the sensor node is very simple: the sensor node is put in a sleep state for a period of 1 second, it is activated by an interrupt request generated by the Real Time Calendar Clock module, then it enters the active phase. During the active period the sensor node executes the SoC measurement routine, acquires a temperature measurement and stores the acquired measurement in the external EEPROM. Finally, it returns in a sleep state. For debug purposes and to validate the proposed SoC measurement procedure, the sensor node provides also a print of some internal variables on the PC.

B. Q_{task} estimate

The process of gathering the Q_{task} values and constructing the look up table to store in the microcontroller memory only needs to be carried out once for each kind of sensor node. The amount of charge drawn by the battery for the execution of each task is obtained by measuring the voltage drop across a shunt resistor of known value and the time duration of the corresponding task with a DSO. After that, voltage measurements need to be divided by the shunt resistance to achieve a current estimation. The current flowing out from the battery during the sleep mode has been measured by a DMM inserted in series between the battery and the board, since the current in the sleep mode results to be too small to be accurately measured by an oscilloscope.

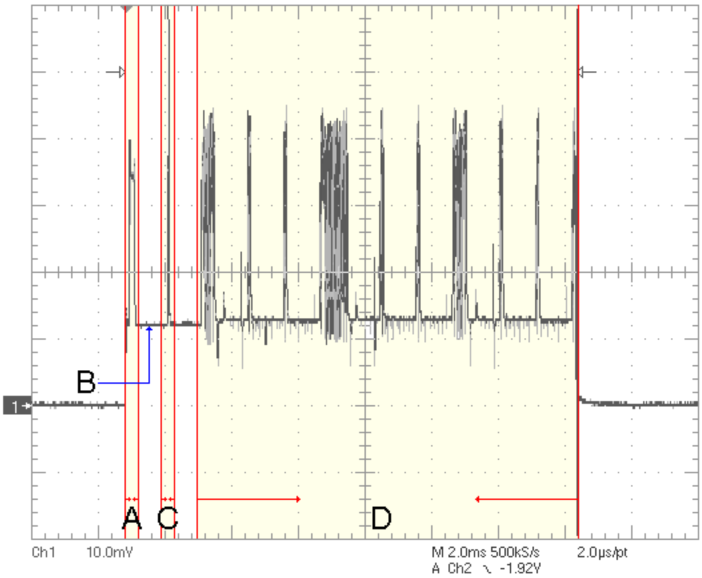

Fig. 3: Oscilloscope screenshot illustrating the behaviour of the voltage drop across the shunt resistor. The current absorbed by the board can be obtained by scaling the voltage with the shunt resistance (about 10Ω).

task	T_{task} **[ms]**	Q_{task} **[µAs]**
A	1.3	2
B	$0.25\cdot10^{-3}$	$0.25\cdot10^{-3}$
C	1.0	2
D	11.3	20
(print)	0.8	10
sleep	10^{3}	1

A = wake-up
B = SoC measurement procedure
C = temperature sensing
D = measurement storing

Table I: Consumption and duration of the main tasks.

Fig. 3 reports the voltage drop across the shunt resistor measured by the oscilloscope during the active phase. Task consumptions can instead be found in Table I. We can note that the measurement procedure for estimating the battery state of charge consumes only 0.25nAs, with a duration of about 250ns, therefore it does not affect the sensor node functionalities and the battery state.

C. $Q_{battery}$ estimate

The amount of usable charge in a Li-Ion battery differs from the available charge. The discharge current is one of the factors that affects the capacity of a battery of delivering charge to the load. In particular, a lower usable charge can be provided to the load in presence of high discharging currents. Furthermore, during the sleep periods a self-recharge process takes place: when no current is being drawn, particular electrochemical reactions around the battery electrodes provide an increment of the available capacity for the next program cycle.
Due to the impossibility of considering these phenomena in sensor nodes, the overall charge that a fully charged battery can deliver to the load - until the battery can be considered almost depleted - needs to be evaluated, in order to correctly initializing the algorithm parameters.
This test consists of discharging a fully charged battery by using the sensor node as a load under normal working conditions. The renewable power source must be switched off to consider only the discharge process. The voltage across battery terminals is measured with a DMM and data are then acquired and stored in a PC. The test is stopped when the measured voltage is lower than 3.0V that represents a safety value for the battery.
In these conditions, the battery is able to power the sensor for a period of about 3500s; in this interval about 350 program cycles are performed. The consumption of one program cycle amounts to about 35uC where 34uC are referred to the active state and the remaining 1uC corresponds to the sleep state (see Table I).
An estimate of the usable $Q_{battery}$ can finally be obtained by multiplying the number of cycles for one cycle energy consumption. This provides a value of about 122.5 mC that corresponds approximately to about 34 µAh.[3]
By comparing this value with the nominal value of the battery reported in the data sheet (i.e., 100µAh) it is possible to see that the usable capacity corresponds to the 34% of the nominal capacity.

D. Example

The results reported in this subsection were obtained by executing the proposed measurement algorithm in a sensor node until the battery was being completely discharged, provided that, at the beginning of the test, the battery was almost completely charged. The firmware running by the sensor node is the same previously

[3] This value results to be very much lower than the nominal battery capacitance since the battery has also been used in experiments in which it had been completely depleted several times.

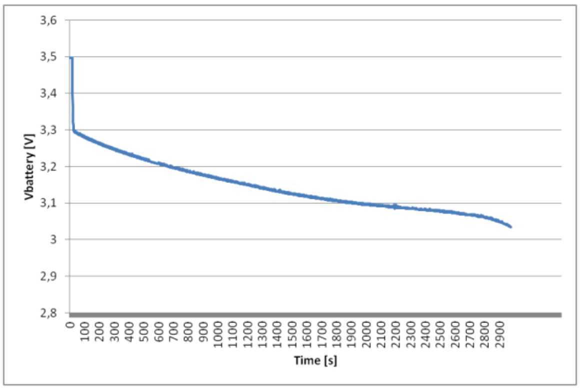

Fig. 4: $V_{battery}$ measured by the ADC of the sensor node.

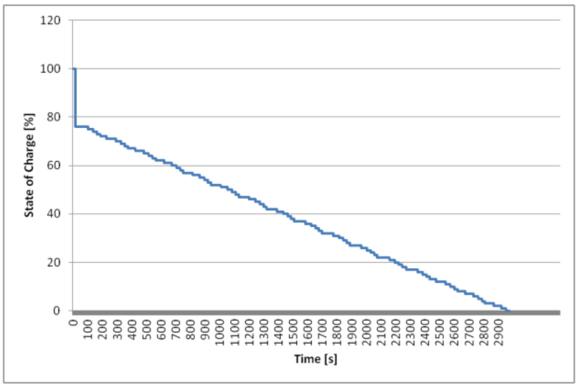

Fig. 5: State of Charge estimated by the sensor node.

described with the prints from the serial interface enabled. Moreover, the renewable power source was being switched off.

Both voltage measurements and SoC estimates have been collected in order to provide a complete characterisation of the proposed measurement system; the results have been reported respectively in Fig. 4 and Fig. 5. We can note that the estimates of $V_{battery}$ follow a behaviour quite similar to the discharge profile: when the battery is almost fully charged the voltage is approximately equal to 3.5V, while it decreases to 3.1V when the battery is discharged.

The estimates of the battery State of Charge are comprised in the range between 100%, corresponding to a fully charged battery and 0%, for a completely discharged battery, which is achieved after about 3000s from the beginning of the test. These estimates present a linear decay over time. This behaviour is justified by the fact that the sensor node executes periodically the same tasks. Different behaviours, more dissimilar from a linear one, can be probably found in sensor nodes whose firmware is based on a more complex finite state machine.

VI. Conclusions

The state of charge estimate of a lithium-based battery is not trivial. Accurate measurements of this quantity require the implementation of complex and expensive - in terms of energy - measuring systems. In a wireless sensor node these methods need to be implemented on-board, thus the energy consumed by the measurement system must be negligible. In this paper we propose a method based on a virtual Coulomb counting, which is able to provide enough accuracy while maintaining negligible the power consumed by the node. Nevertheless it requires a preliminary characterization of the sensor node behavior through laboratory tests and a careful initialization of the variables to obtain meaningful results. In future works, also the charging process, that at the current moment it has been considered only in simulation, will be taken into account.

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