State-of-charge estimation to improve decision making by MAC protocols used in WSNs

V. Quintero✉, A. Perez, C. Estevez and M. Orchard

Energy conservation is a topic of great interest in wireless sensor networks (WSNs). Various techniques have been proposed to minimise the energy consumption. One approach is to design medium access control (MAC) protocols capable of adjusting the sensor node cycle according to the available energy in the battery. The state of charge (SOC) is an indicator of the available energy stored in the battery before discharging. This work proposes a simplified battery model to estimate the SOC and compares the accuracy and computational load of the algorithm as metrics for the implementation of the MAC protocol design.

Introduction: Wireless Sensor Networks (WSNs) are frequently used in monitoring applications (e.g., environmental phenomena and health-care). Traditionally, these types of networks are energised with batteries, which are known to have a limited lifetime [1]. This situation is one of the reasons why the conservation of energy in WSNs is a critical research topic. To address this issue, WSNs are incorporating the use of Energy Harvesting Devices (EHDs), which are capable of delivering energy to the network sensors allowing the battery to recharge. Knowing the amount of energy available in the battery of sensor nodes, contributes to the adjustment of the operating cycle through MAC protocols, preventing the battery to be depleted below safety levels. The design of MAC protocols with dynamic operating cycles is one of the techniques implemented for the conservation of energy in WSNs. Several MAC protocols incorporate information from the battery [2, 3], where two different techniques can be used to estimate the amount of energy remaining in the battery. The SOC can be defined as the amount of energy that a battery can deliver until it reaches its End-of-Discharge (EoD) time [4]. The SOC estimation provides information of great importance to the MAC protocol, since it creates awareness of which sensor nodes have less energy. With this information, the protocol prioritises the transmission of information while it does not exceed the battery's operating safety level (that is, it reaches the level at which the battery suffers irreversible damage to its chemistry). Hence the selection of the SOC estimation method is relevant.

Methodology: Currently, various models have been proposed to characterise the battery behaviour when discharging, as physical, empirical, abstract, electrochemical, electrical, and stochastic. The first step of the proposed methodology is to simplify the empirical battery model presented in [3, 5]. This model uses the open circuit voltage (OCV) curve to establish the measurement equation, which is the equation that allows updating the voltage values to adjust the SOC estimation. In this work, to simplify the model, it is proposed to avoid the zone of the OCV curve in which the voltage has an abrupt drop. Removing this area ensures that the battery remains within its safety levels. The OCV curve is defined between $3.6 \leq V \leq 4.2$, where 4.2 V is the maximum battery voltage (see Fig. 1).

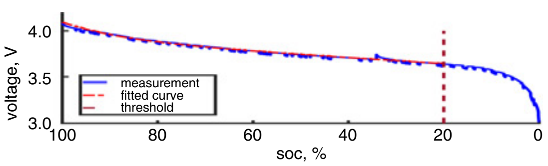

Fig. 1 *OCV curve during the discharge process*

The state-space model is defined according to (1)–(3). Since the voltage is constrained, the measurement equation proposed in [3, 5] is simplified, and it is defined according to (3). In this state-space model, x_1 is associated to an unknown parameter related to the internal impedance of the battery, x_2 corresponds to the SOC measurement, $i(k)$ and $v(k)$ refer to the current and voltage of the battery, $\omega_1(k)$ and $\omega_2(k)$ are the process noises, and $n(k)$ is the observation noise. The parameter v_o is the OCV when the battery is fully charged, v_l is the y-intercept of the extrapolation of the zone defined for $0.25 \leq \text{SOC} \leq 0.70$. The variables γ and α are configurable design model parameters and E_{crit} is the total energy delivered by the battery.

State transition equations:

$$x_1(k+1) = x_1(k) + \omega_1(k) \tag{1}$$

$$x_2(k+1) = x_2(k) - v(k)i(k)\Delta t\, E_{\text{crit}}^{-1} + \omega_2(k) \tag{2}$$

Measurement equation:

$$\begin{aligned} v(k) = {} & v_l + (v_o - v_l)e^{\gamma[x_2(k)-1]} + \alpha v_l[x_2(k) - 1] \\ & - i(k)x_1 + n(k) \end{aligned} \tag{3}$$

The second step is to estimate the SOC of the battery. In this work, two methodologies are used to estimate the SOC based on the OCV curve. The first methodology was presented in [3, 5] and in this article is referred as M_1(although the OCV curve is constrained as explained previously). In M_1 the SOC estimation is based on the Particle Filter and it uses the model described in (1)–(3) to characterise the battery behaviour. The second methodology used, M_2 [2], defines the voltage as a function of time using a polynomial expression. To estimate the SOC it is necessary to determine the amount of energy consumed in an operating cycle. In this article, an operating cycle is defined by the alternation between two current levels (22 and 14 mA) (see Fig. 2). In addition, for comparison purposes, a third methodology, M_3, is incorporated in this article. M_3 is similar to M_1 and with the exception that the entire OCV curve is used, this means there are no restrictions.

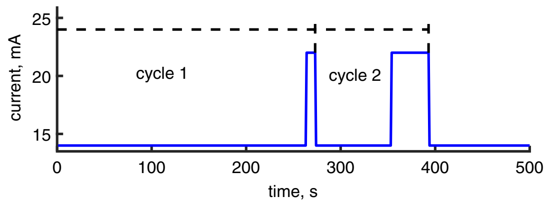

Fig. 2 *Definition of operation cycle*

The last step is to compare the methodologies (M_1, M_2, M_3) to estimate the SOC, and use this result to quantify both the root-mean-square error (RMSE) and the processing time to obtain the estimation. In addition, these methodologies are studied to observe their behaviour when changing the battery usage profile. In this case, the current profile required by the battery during a time period is modified using a Markov chain method.

Results: The database used corresponds to the voltage and current data obtained from the complete discharge of a rechargeable lithium-ion battery type LIR2032 (nominal values of 45 mA and 3.6 V) [4]. In this work, M_1 and M_2 are used to estimate the SOC of the battery. It is imperative that the first step is to determine the equation and model parameters of both methodologies. For M_1, the model parameters are determined off-line to fit the variables of the state-space model of (1)–(3), which describe the OCV curve of Fig. 1. The results are shown in Table 1.

Table 1: Model parameters for battery LIR2032

Battery	v_o	v_l	α	γ	E_{crit}
LIR2032	4.0487	3.894	0.08353	7.635	534

M_2 defines the voltage of the battery according to (4). The amount of energy consumed in an operating cycle (E_{cycle}) is defined by (5), where P_{tx} and P_{rx} are the powers associated with the transmission and reception mode of the sensor node, respectively, and $V(t)$ is the voltage measured in the corresponding time intervals

$$V(t) = 4.446e^{-9}t^2 - 8.517e^{-9}t + 4.023 \tag{4}$$

$$E_{\text{cycle}} = \int_{t_0}^{t_1} \frac{P_{tx}}{V(t)}\text{d}t + \int_{t_1}^{t_2} \frac{P_{rx}}{V(t)}\text{d}t \tag{5}$$

Once the equations and parameters of the model are defined, the algorithms are executed to estimate the SOC. Both methodologies use the restriction $V_{oc} \geq 3.65$. The first results obtained correspond to the voltage and SOC estimation of the battery using the three models (M_1, M_2, M_3) (see Figs. 3 and 4). In both figures it is observed that M_1 and M_3 achieve a better estimation of the voltage and SOC than M_2.

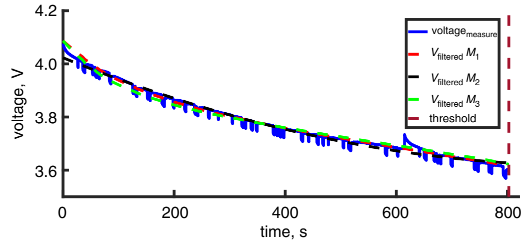

Fig. 3 *Voltage estimation using the three methodologies*

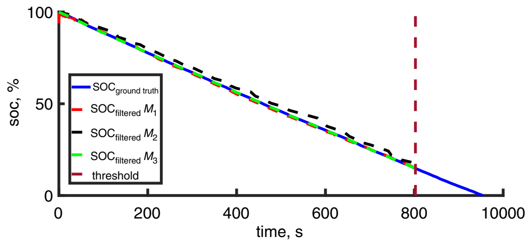

Fig. 4 *SOC estimation using the three methodologies*

Table 2 shows the RMSE and the processing time obtained for three iterations of each of the methodologies M_1, M_2, and M_3. When M_1 is compared to M_2, it can be clearly noted that M_2 has a faster processing time. Regarding the accuracy, M_1 presents a better performance than M_2, due to a smaller RMSE. These two facts are supported with the results of all three iterations. Furthermore, after 50 iterations of each methodology, results for M_1 show a mean value for the RMSE of 0.0092 and a standard deviation of 0.0061. Note that the RMSE of M_2 does not change and the variations in the processing time are minimal. On the other hand, if the SOC estimation is implemented according to M_3, the performance of the method is similar with M_1, since M_1 is just a simplification of M_3. Hence, the processing time is almost the same between M_1 and M_3, although the RMSE is smaller with the use of the simplified model. In other words, the accuracy obtained is better when M_1 and M_3 are used even though the processing time remains approximately seven times greater than the obtained with M_2.

Table 2: Comparison metrics

Iterations	Methods	RMSE	Processing time, ms
1	M_1	0.0078	834
1	M_2	0.0153	101
1	M_3	0.0122	832
2	M_1	0.0098	825
2	M_2	0.0153	105
2	M_3	0.0097	825
3	M_1	0.0044	823
3	M_2	0.0153	101
3	M_3	0.0052	824

The adaptability of both methods is studied changing the usage profile. Using a Markov chain method, two different current profiles are generated. To create the two-state Markov chain, the methodology proposed in [6] and the current levels mentioned in Fig. 2 are used. Also, the corresponding transition matrix is estimated through the maximum likelihood estimator [6], and it is defined as follows:

$$\boldsymbol{M}_T = \begin{pmatrix} 0.9933 & 0.0320 \\ 0.0067 & 0.9680 \end{pmatrix} \quad (6)$$

Table 3 shows the results obtained when executing the algorithms with the current profiles obtained with the Markov chain method. Analysing the RMSE obtained for each of the cases, it is confirmed that M_2 cannot adjust to the changes in the current profile because the equation that defines the voltage is a function of time, so the model depends on the discharge current used. On the other hand, method M_1, which is similar to M_3, has the capability to make the future operation of the battery independent from the past.

From the information obtained above, several considerations can be made for the design of the MAC protocols. The selection of the SOC estimation method will depend on the type of application where the MAC protocol is used and the processing capacity of the network sensor nodes. For example, if the MAC protocol implemented in the WSN involves a large computational overhead, it is possible to opt for a lower processing SOC estimation algorithm like M_1 considering the error margin present when determining the battery EoD time. On the other hand, if the computational overhead contained in the sensor node is high, it is possible to implement, within the MAC protocol, an algorithm for SOC estimation, for instance M_1. The more accuracy on the SOC estimation results in a better assessment of the amount of energy available in the battery.

Table 3: RMSE changing the usage profile

Iterations	Methods	RMSE	Processing time, ms
1	M_1	0.0063	827
1	M_2	0.0153	101
1	M_3	0.0091	832
2	M_1	0.0086	831
2	M_2	0.0153	105
2	M_3	0.0115	831

Conclusion: In this work, a simplified model of the battery is proposed to estimate the SOC of a lithium-ion type LIR2032 rechargeable battery. The simplification of the model does not represent a reduction of the processing time, but an improvement in the accuracy of the SOC estimation. This aspect is important to be able to determine with greater accuracy the EoD time of the battery. The decision-making process to adjust the operation cycle of a sensor node is improved when the MAC protocols take into account the battery SOC estimation. This is possible by having knowledge of the amount of remaining energy in the battery. The SOC estimation is carried out by means of two methods with different processing time and accuracy, thus establishing metrics that collaborate in the design of the MAC protocols for WSN. The selection of the SOC estimation method of the battery is subject to the type of application and the technological resources that the sensor nodes have.

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One or more of the Figures in this Letter are available in colour online.

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