NICD BATTERY DISCHARGING ESTIMATION SYSTEM FOR AGVS WORKING IN INTELLIGENT WAREHOUSES BASED ON EKF

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Abstract. *A relevant issue in the literature about the routing and control of AGVs (Automated Guide Vehicles) is the battery management. In intelligent warehouses and automated logistics systems, the use of batteries may have serious impacts on the system and AGV availability, such as throughput times and number of AGVs required. In AGV systems, the basic precondition for the functioning is a suitable and constantly available power supply. Thus, warehouse automated systems need to take into account that AGV usually use batteries. AGVs travel long distances and, as a result, have short idle times, when traveling relatively short distances, batteries can be replaced or charged, and the time required to execute these operations might impact on the performance of the system. The function of battery management is to ensure that batteries have sufficient charge to perform the current task of the mini-robotic forklifts. In this context, this paper proposes a battery discharging estimation system to estimate the mini-robotic forklifts consumption for a certain route and verify the available charge capacity. To approach the management battery in AGVs it is necessary to control the battery functioning. Firstly, the mini-robotic forklift battery was characterized through discharge tests with different load and rates profiles. The battery discharge tests were performed experimentally using an acquisition system, and the voltage and current data were collected in a log. From this log, we proceeded an offline estimation of the unknown battery parameters. With these parameters, the mathematical model was implemented in the Extend Kalman Filter method to estimate the SOC (State of Charge) online. The method applied to estimate SOC was validated through discharge operation tests in mini-robotic forklift battery. The proposed system allowed to estimating the charge battery consumption used by the mini-robotic forklift to perform a task assigned by the routing system.*

Keywords: *state of charge, management battery, EKF, intelligent warehouse, AGV.*

1. INTRODUCTION

A relevant issue in the literature about routing and control of AGVs (Automated Guide Vehicles) is the battery management. The battery management system is a device that manages a rechargeable battery (cell or battery pack) by monitoring its state. The battery must be reliable and capable of delivering enough energy when required. The State of Charge (SOC) is an important feature to evaluate the battery. The management system can monitor the consumption of the battery represented by State of Charge (SOC) to indicate the level of battery charge (Piller *et al*., 2001). The SOC can be regarded as the ratio of the stored charge available relative to that available full charge of a battery, indirectly indicating the operation scope of an AGV (Zhang *et al*., 2010).

The accurate SOC estimation is one of the main tasks of battery management systems, which will help improve the performance and reliability of the vehicle (Zhang, 2008). It will also ultimately lengthen the lifetime of the battery (Bhangu *et al*., 2005), as it allows the battery to be used within its design limits, avoiding over-discharge (Kim, 2007).

Concerning applications to intelligent warehouses, the use of batteries may have serious impacts on the routing system and AGV availability, such as throughput times and number of AGVs required. The AGVs travel long distances and, as a result, have short idle times, or travel relatively short distances and during idle times batteries can be replaced or charged. However, the basic precondition for the functioning of AGV system is a suitable and constantly available power supply. Few researches have presented studies about battery management (Vis, 2006), since it is a commonly omitted aspect in the AGVs systems (Maza and Castagna, 2002; Möhring *et al*. 2004; Klimm *et al*., 2007; Gawrilow *et al*. 2008; Raviza, 2009; Vivaldini, 2010). Obviously, vehicles have to be charged after a certain operating period, but most researches on AGVs assume that the battery problem has little effect on the performance (Le-Anh and Koster, 2006). In order to address the battery management issue in routing systems for AGVs it is necessary to control the battery operation (Vis, 2006).

This work is part of researches on robotic forklifts for intelligent warehouses developed at the Mobile Robot Laboratory at USP–EESC in Brazil. In previous works, we have developed routing, navigation and auto-localization systems in a simulated environment. For the real implementation of mini-robotic forklifts (Figure 1) in a scaled environment, the routing system must ensure the execution of tasks estimating the remaining battery power of each robotic forklift. Thus, it will be necessary to obtain the battery SOC of mini-robotic forklifts and estimate of battery

consumption to perform a certain task assigned by the routing system. For the immediate displaying of the SOC to the routing system, the knowledge of the remaining battery capacity is of importance for its management.

Figure 1. Mini-robotic forklift

To attribute the tasks that will be performed by the robotic forklifts, the routing system must verify if the updated SOC is compatible with the estimated consumption. In this context, this paper proposes a method to estimate SOC using Extend Kalman Filter (EKF) and the routing task actuation log to preview the battery consumption.

Firstly, it is necessary to characterize the mini-robotic forklift battery (as specific type) through discharge tests of battery with a moderate rate profile. The moderate rate profile is used because, according to Plett (2004a), battery electric vehicles operate within this profile.

The battery discharge tests were performed experimentally, as shown in Figure 2. The data of voltage/current were collected in a log using an acquisition system. From this log, we proceeded an offline estimate of the unknown battery model parameters.
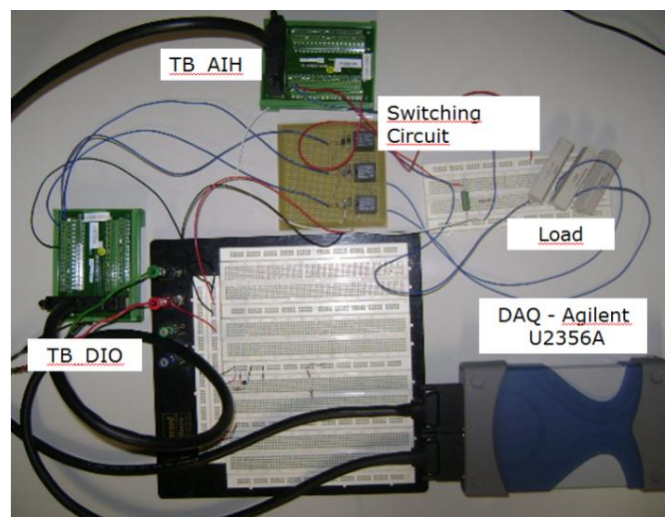

Figure 2. Experimental test

Based on these parameters of the mathematical model, EKF method was implemented to estimate the SOC online. This method deals with model uncertainties and noise sensor of the physical system. Some works use this method for SOC estimate (Plett, 2004a; Plett, 2004b; Plett, 2004c; Shi and Zhao, 2006; Qi *et al*., 2008; Knauff *et al*., 2010), and it has been proved effective for this type of application, differently from dedicated hardware solutions (i.e. fuel-gauge and battery charge management controller or supervisor), which show the current situation of the charge of battery without prediction and estimate of SOC.

The charge consumption of the forklift battery varies according to the operation performed. Therefore, a system based only on Open Circuit Voltage (OCV) is not adequate to estimate the charge that remains in the battery.

The method applied to estimate SOC was validated through an experimental test of the discharge operation of mini-robotic forklift battery. In this test, we use a load resistors simulating the equivalent consumption of sensors, motors and drives control utilized in the mini-robotic forklifts, as shown in Tab 1.

Table 1. Components of mini-robotic forklift.

Component	Description	Power (Vdc)	Total nominal current [A]
1 Laser	Hokuyo URG-04LX	5	0.5
8 Sonar:	LV MaxSonar EZ-01	2,5 - 5,5	0.016
1 Fork motor	RE-max 17/4,5 216010	12	0.414
2 Wheel motor	RE-max 29 226802	12	2.16
1 EPOS 24/1		9 – 24	0.15
2 EPOS 24/5		11-24	0.3

The load resistors are activated by the acquisition system, according to the actuation log of forklift components. This actuation log is generated by the routing system to perform a certain route. The system allows estimating the battery consumption for a certain route. The estimated consumption can be compared with the SOC obtained from the EKF. However, is possible to verify the available load capacity of a mini- robotic forklift to perform a task assigned by the routing system.

This paper is organized as follows: in Section 2, the Nicd battery pack is modeled and subsequently the EKF-based method is applied to estimate battery pack SOC in Section 3. The experimental results and conclusion are given in Sections 4 and 5, respectively.

2.TEST BENCH

The block diagram of the implemented battery test-bench is shown in Fig. 1. All tests developed in a test-bench were designed to study the behavior of NiCd batteries capacity under fast-charging.

Charging and discharging processes were performed using programmable systems (DC Power Supply and DC Electronic Load) in order to obtain high flexibility in the test design.

The main battery parameters (battery voltage and current) were sampled to provide information about the battery's behavior, specially under high charging rates. A Data Acquisition Unit was employed to signal conditioning. All equipment was connected to the personal computer through USB port. The equipment control and data processing were implemented using LabVIEW Software (Laboratory Virtual Instrument Engineering Workbench).
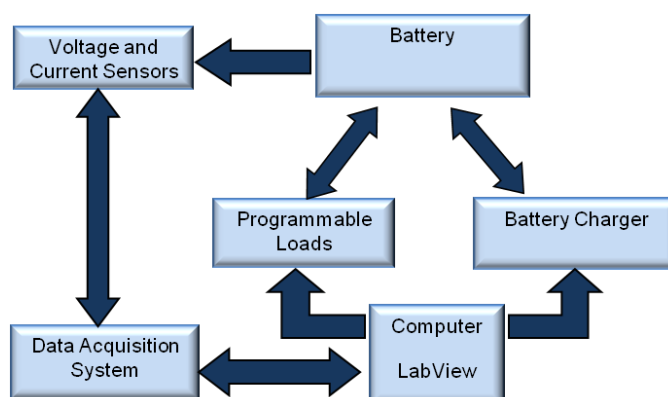

Figure 1. Test-bench block diagram.

The sampled data were processed and monitored on-line on the personal computer. Therefore, all types of fast-charge methods and fast-charge end detection methods could be implemented.

2.1 Test bench description

The test bench built to acquire the battery voltage and current parameters was based on direct voltage measurements and a low side current shunt sensor resistor. The schematic signal conditioning circuit is shown in Figure 3. A shunt sense resistor (R_Sense) of 0,01 Ohm, a 0,5% precision and 5W nominal power was used as the current sensor.
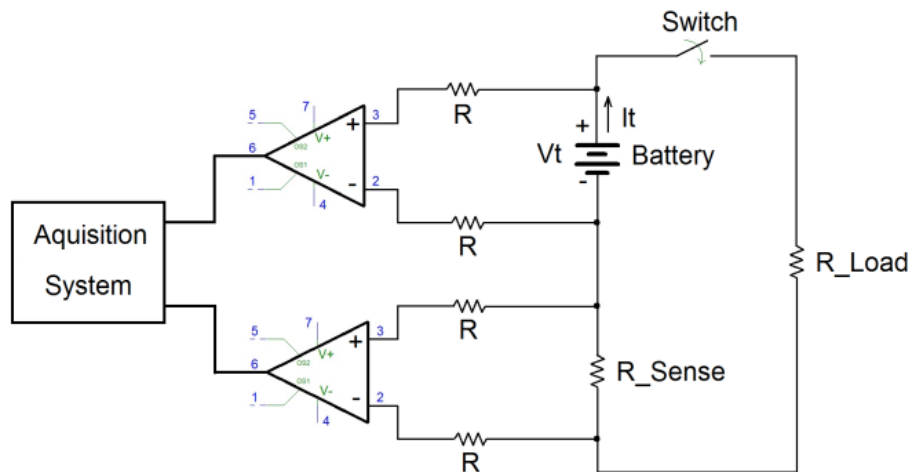

Figure 3. Schematic signal conditioning circuit

A Nick Cadmium battery pack of HTR9018 - Radiocell (Figure 4) of 1,2 Ah nominal capacity, 7,5 V nominal voltage and 5V nominal cut-off voltage was tested in the experiment proposed.


Figure 4. Battery pack

In this experiment, the battery powers a load resistance (R_Load) of 4,7 Ohm and nominal power of 20W, simulating a discharge profile of 1,16 C. The battery discharges from fully charged to fully discharged, therefore a 1-minute current pulse and a 1-minute rest are applied to the battery cell during the discharge process. The data sampling rate was set to 100Hz.

The parameter results are shown in Figure 5.
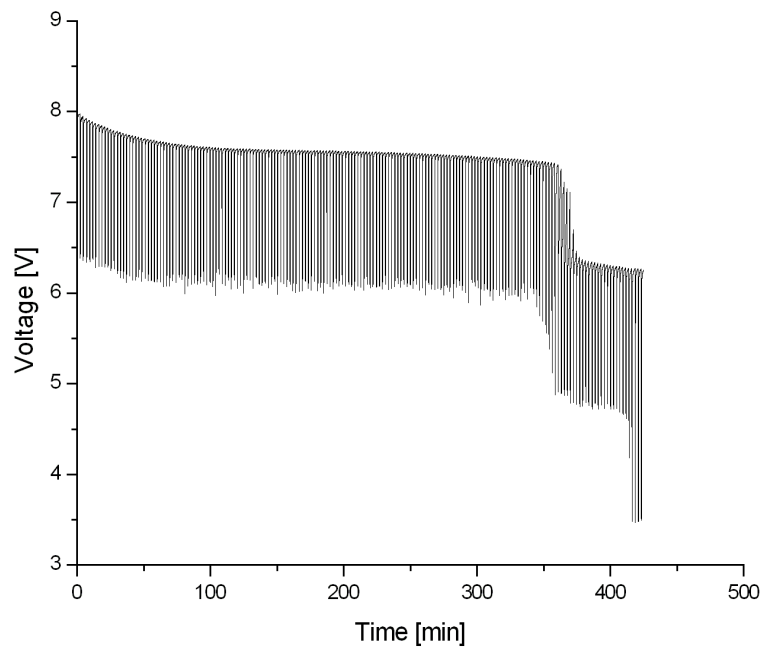
(a)
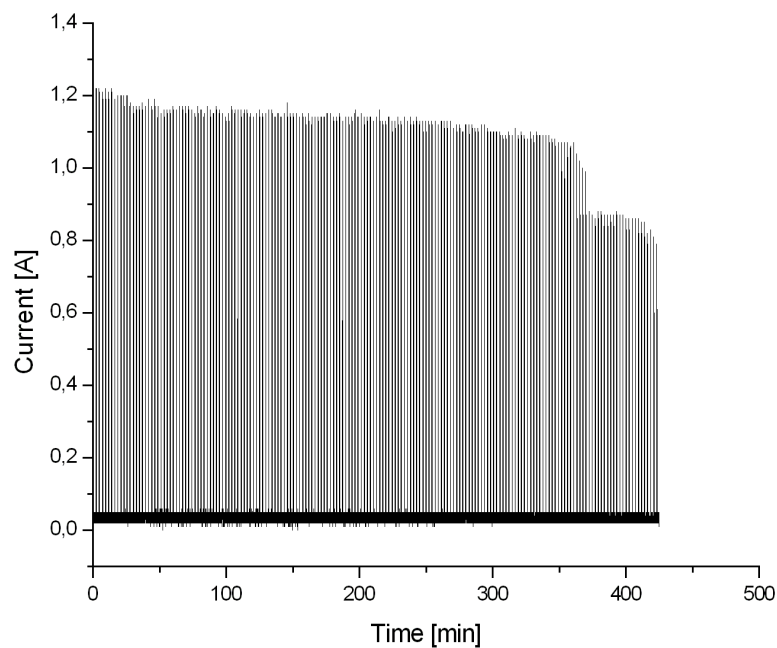
(b)

Fig. 5. In: (a) Measured terminal battery cell voltage; in (b) Measured terminal battery cell current

3. EKF FOR SOC ESTIMATION

In the EKF technique, a linearization process is performed at every time step to approximate the nonlinear system by a linear time varying system, which is then used in a KF, resulting in an EKF for the true nonlinear system (Zhang *et al.*, 2008). The EKF uses the measured input and output to find the minimum mean squared error estimate x of the true state x , with the assumptions that the process noise and sensor noise are independent zero-mean Gaussian noises (Wang *et al.*, 2010). Although EKF approximates the nonlinear system with a linear time varying system, its effectiveness has

been verified in many works (Vasebi, 2008, Bhangu *et*. al, 2005; Plett, 2004c; Plett, 2004a).

In order to use the EKF for the battery SOC estimation, we chose the cell combined model described by Plett (2004b) and adopted by Shi and Zhao (2006) in the implementation of the Unscented Kalman Filter (UKF):

$$z_{k+1} = z_k - \left(\frac{\eta_i \Delta t}{C_n}\right) i_k \tag{1}$$

$$y_k = K_0 - R i_k - \frac{K_1}{z_k} - K_2 z_k + K_3 \ln(z_k) + K_4 \ln(1 - z_k) \tag{2}$$

where z_k represents the SOC at any time state, η_i is the cell coulombic efficiency, $\eta_i = 1$ for discharge and $\eta_i \leq 1$ for charge (Plett, 2004b), C_n is the cell nominal capacity or initial electric full charge capability, i_k is the instantaneous cell current, assumed positive for discharging and negative for charging, Δt represents the sample time period, y_k is the predicted terminal voltage, R is the battery internal resistance, and K_1, K_2, K_3 and K_4 are constants chosen to make the model fit the acquired data through the least-squares estimation.

3.1. Least-squares estimation

With a set of $\{y_k, i_k, z_k\}$ from the log of cell tests, we obtain vector (3) and calculate matrix (4) using equation (5).

$$Y = [y_1, y_2, \ldots, y_n]^T \tag{3}$$

$$H = [h_1, h_2, \ldots, h_n]^T \tag{4}$$

$$h_j^T = \left[1, i_j^+, i_j^-, \frac{1}{z_j}, z_j, \ln(z_j), \ln(1 - z_j)\right] \tag{5}$$

$$\theta^T = [K_0, R^+, R^-, K_1, K_2, K_3, K_4] \tag{6}$$

$$\theta = (H^T H)^{-1} H^T Y \tag{7}$$

We solve vector θ of unknown parameters in (6) using the known matrices Y and H by means of equation (7). Tab. 2 shows the parameters obtained after applying the method to the lithium polymer battery data log.

Table 2. Combined model parameters.

K_0	R^+	R^-	K_1	K_2	K_3	K_4
8.3656	-1.3416	-1.2141	0.0006	-0.8834	0.5573	-0.1022

3.2. EKF Algorithm

The EKF algorithm is divided into two steps (prediction and correction), and composed of equations (9) to (13), adapted from Thrun (2006) EKF algorithm.

Input:

$$\mu_{t-1}, \Sigma_{t-1}, u_t, s_t \tag{8}$$

Prediction:

$$\bar{\mu}_t = g(u_t, \mu_{t-1}) \tag{9}$$

$$\bar{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + R_t \tag{10}$$

Correction:

$$K_t = \bar{\Sigma}_t H_t^T (H_t \bar{\Sigma}_t H_t^T + Q_t)^{-1} \tag{11}$$

$$\mu_t = \bar{\mu}_t + K_t (s_t - h(\bar{\mu}_t)) \tag{12}$$

$$\Sigma_t = (I - K_t H_t)\overline{\Sigma}_t \tag{13}$$

Return:

$$\mu_t, \Sigma_t \tag{14}$$

Given an initial state vector (μ_{t-1}) and a control vector (u_t) from the (8), the algorithm predicted of the mean value of the actual state vector variables ($\overline{\mu}_t$) using function $g(.,.)$ in (9). For the combined model structure, the state vector has only the SOC as state ($\mu_t = z_k$). Equation (10) computes the predicted covariance matrix ($\overline{\Sigma}_t$) using the input covariance matrix (Σ_{t-1}), the jacobian matrix (G_t) of $g(.,.)$ and the process noise matrix (R_t).

The correction step compute the Kalman gain in equation (11) using the jacobian matrix (H_t) of $h(.)$ and measurement noise matrix (Q_t). In (12) and (13) the new state vector (μ_t) and the new covariance matrix (Σ_t) are computed. The difference $(s_t - h(\overline{\mu}_t))$, called innovation, corresponds to the difference between the measurement vector (s_t) and the predicted measurement $h(.)$. In the combined model s_t is the voltage in the battery terminals and $h(.)$ is equal to y_k of the model equation (2).

In (14) the algorithm finally returns the state vector and the covariance matrix, and these values are used in the next algorithm iteration.

4. ON-LINE SOC ESTIMATION

The function of battery management is to ensure that batteries have sufficient charge to perform the current task of the mini-robotic forklifts. Therefore, an on-line estimate was performed, as shown in Figure 6. The routing system provides an actuation log containing data related to the components of Tab. 1. This actuation log indicates which components are on/off for each time interval t ($\Delta_t = 0,5 \ s$) during the performance of a determined route.

The acquisition system reads and synchronizes the battery discharging through the actuation log. The battery is discharged by a switching circuit, which each instant turns on/off the loads according to the actuation log of forklift components. At the same time, the acquisition system performs the reading of voltage and current parameters provided to the EKF to estimate the SOC.
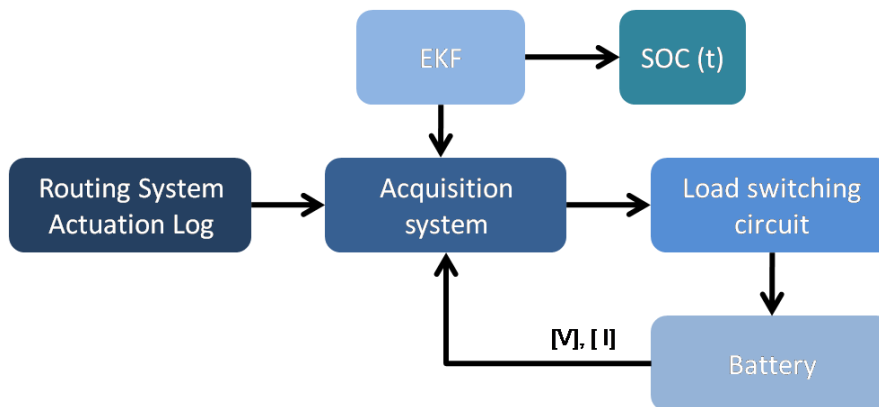

Figure 6. On-line estimation

5. RESULTS

In this experimental test, some tasks were assigned to a mini-robotic forklift by a routing system. The actuation log contains the operation of motors and sensors according to the implementation of the route. Tab. 3 shows the tasks.

An experimental test using the log of routing system was carried out in a simulated environment Player/Stage (Gerkey, 2003) to show the route (Figure 7) performed by the mini-robotic forklift (Tab. 3), we used the

The experimental test simulating the discharge operation of a mini-robotic forklift battery validated the method applied to estimate SOC. In this test it was possible to estimate the battery consumption for this route (20 min), and consequently, validate how long it would take the battery to perform the tasks. Thus, in a certain percentage of the SOC when the battery needs recharging, this information is sent to the routing system. It can be possible to assign and redirect tasks for robotic forklift according to their power battery capacity.

Table 3. Route for one forklift

| TASK	POINT		TYPE OF TASK
	Origin	Destination	
Depot			Without task
Task 01	Shelf-B14	Charging F	Loading/Unloading
Task 02	Shelf-B14	Charging F	Loading/Unloading
Task 03	Shelf-B14	Charging F	Loading/Unloading
Task 04	Shelf-B14	Charging F	Loading/Unloading
Task 05	Production_B	Shelf-E03	Loading/ Unloading
Task 06	Production_B	Shelf-E03	Loading/ Unloading
Task 07	Production_B	Shelf-E03	Loading/ Unloading
Task 08	Production_B	Shelf-E03	Loading/ Unloading
Task 09	Shelf-D01	Charging_B	Loading/ Unloading
Task 10	Shelf-D01	Charging_B	Loading/ Unloading
Task 11	Shelf-D01	Charging_B	Loading/ Unloading
Task 12	Shelf-D01	Charging_B	Loading/ Unloading
Depot	Depot		Return
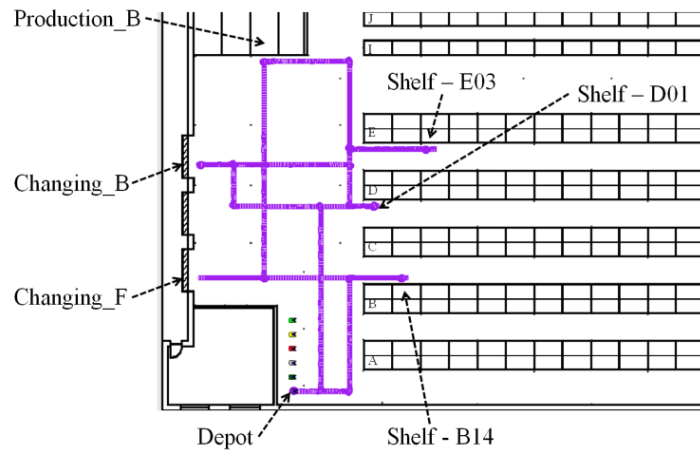
Figure 7. Illustration of route executed by a forklift

Figure 8 shows the SOC values using the EKF-based method (SOC EKF) and Open-Circuit Voltage relationship (SOC OCV). The OCV is the terminal voltage when there is no load connected and no external current applied to the battery. The relationship between OCV and SOC is determined by measurements (Xiao, 2010). As the NiCd battery pack does not have a deep discharge protection circuit, the battery continues supplying power at useless level for the application. In our tests, the discharge occurs in the first 5 minutes.
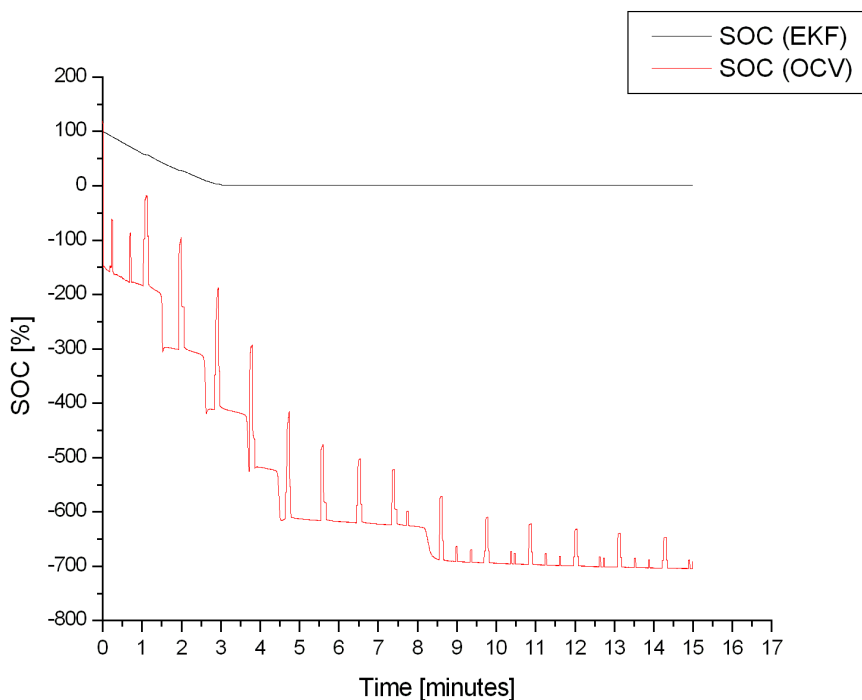
Figure 8. SOC EKF versus OCV

As we can see, the SOC values based on OCV are not real when there are loads connected. Therefore in applications that require an SOC online estimate without operation interruption, the SOC EKF estimate presented in this paper is more suitable.

6. CONCLUSIONS

The battery management system proposed allows estimating the battery consumption for a certain route. Through monitoring it is possible to deploy other features associated with the routing system, such as failures anticipation related to lack of forklift energy, and adaptation of activities to be performed according to the battery SOC. This process allows taking preventive actions, improving the system's performance.

In future works, the battery management system will be embedded in the mini-robotic forklift of LabRoM and also integrated with our routing system through SOC reports.

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