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Battery Identification With Cubic Spline and Moving Horizon Estimation for Mobile Robots

Mohammad Shokri¹, Lorenzo Lyons², Sérgio Pequito³, *Senior Member, IEEE*, and Laura Ferranti⁴

Abstract—We propose a novel approach to track the state of charge (SoC) of batteries in mobile robots to improve their capabilities. The batteries' status is critical to accomplish their mission, but limited battery life can be a challenge. Our methodology focuses on modeling and estimating the SoC of batteries through system identification and fractional-order models. These models are flexible and can adjust to transient responses, allowing for accurate estimation of battery characteristics. Specifically, we use cubic spline interpolation to obtain the open-circuit voltage (OCV) and the different resistors of the battery model. To estimate the SoC, we deploy a novel approach based on the moving horizon estimation (MHE) algorithm, which is suitable for handling poor initial estimation and constraints on the battery model. We consider the constraint on the peak discharging current, which can limit the performance of mobile robots in low-battery mode. We validate our approach by applying system identification and MHE to data from a mobile robot. The results show that our method accurately estimates the SoC despite poor initial values, enabling improved performance for mobile robots.

Index Terms—Battery model, cubic spline, fractional-order models, moving horizon estimation (MHE), system identification.

I. INTRODUCTION

MOBILE robots have the potential to improve our quality of life in many applications such as warehouse logistics [1], scene reconstruction [2], and search-and-rescue [3]. To operate, mobile robots depend on their onboard battery. Thus, it is essential for mobile robots to monitor the battery's state of charge (SoC) in terms of percentage to fully charged to ensure successful completion of their missions [4], [5].

Because there is no sensor for measuring the SoC directly, the SoC can be considered as a hidden state of the battery that has to be estimated based on the observed data from the battery, such as the terminal current and voltage. Therefore, it is crucial to have a reliable battery model to estimate the SoC through current and voltage measurements. In particular, it is important for the mobile robot's batteries, which may have different behaviors connected to other electrical devices, such as motor drivers or electrical converters [6].

There are many data-driven approaches for modeling batteries that consider an electrochemical model whose parameters

are obtained via system identification [7], [8]. Another approach is the equivalent circuit model (ECM), where the battery model consists of the open-circuit voltage (OCV) and some electrical circuits to model the transient response [4], [5], [9]. In [9], the curve for the OCV is assumed to be available, and the authors obtain the parameters of the RC circuits. Especially, this assumption is essential for recursive least-square approaches which are sensitive to initial conditions for compensating errors [10]. In [11] and [12], a parametric model is considered for the OCV curve, which is made by some fixed functions. Toward a more flexible structure for the OCV, Kwak et al. [13] and Chen et al. [14] leverage a piece-linear interpolation that considers linear functions between every two consecutive points and can be fit with data.

To model the temporal behavior of batteries, a chain of fixed RC circuits is exploited to model slow and fast transient responses [14], [15]. The work in [16] and [17] considers RC circuits to depend on the SoC to model different temporal behavior in low-battery or high-battery modes. To extend the temporal flexibility, fractional-order calculus has attracted increasing interest for modeling batteries [18], [19]. In fractional-order models, fractional-order RC circuits (FRCCs) have been considered, in constant phase elements with fractional-order derivatives [20], [21]. Constant phase elements represent the electrochemical dynamics of the battery and can behave like ideal capacitors or resistors depending on their order of derivatives [22].

Given the battery model, there are a variety of approaches for estimation the SoC. The extended Kalman filter (EKF) is a popular method for SoC estimation because of the nonlinearity of the battery model [23], [24]. An unscented Kalman filter (UKF) is also useful for estimating SoC since it can estimate the mean and covariance of error more accurately than EKF [4]. In [19], UKF is used for the fractional-order battery model. However, EKF and UKF misperform when the initial value of the estimation is far from the real value of SoC [25]. In addition, they cannot handle the constraints and may estimate an infeasible SoC. An intrinsic limitation exists on the maximum deliverable power that is reduced in low-battery mode, and the battery cannot provide any current while it is in low-battery mode [26], [27]. Thus, the constraint on SoC and the peak current should also be considered in SoC estimation [11], [16], [26], [27].

Moving horizon estimation (MHE) is an estimation method that is able to cope with the aforementioned issues faced by Kalman-based estimations such as EKF or UKF. Specially, MHE solves a constrained optimization problem to estimate SoC in a time-receding fashion. The works in [7], [8], and [25]

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apply MHE to the battery model with the integer-order model. In this brief, we exploit MHE for a fractional-order battery model to consider the dynamics of FRCC and to factor in the low-battery mode constraint. In particular, we propose a fractional-order battery model with flexible structures for an SoC–OCV curve, a resistor, and multiple FRCCs whose resistors depend on the SoC to consider different behaviors in the SoC range.

To characterize the dependencies of SoC, the OCV and the resistance (of the resistor and the FRCCs) are considered to be curves of SoC. For curve formulation, we use cubic splines, which apply cubic polynomials between each pair of consecutive points to produce smooth and differentiable curves [28]. This method imbues our model with exceptional flexibility, enabling it to adeptly adjust to various environmental conditions. Then, we investigate the peak discharging current of the battery based on the available data. Afterward, given the battery model, we propose an MHE framework for the SoC and FRCCs' states by considering the SoC range constraints and the constraint of the peak discharging current. MHE minimizes the errors of the terminal voltage, the SoC dynamics, and the truncation errors made by fractional-order states.

This brief's contributions are as given below.

- 1) Application of fractional-order calculus to model a mobile robot's battery, including SoC-dependent curves for the OCV, resistor, and FRCCs, with higher description capabilities and, therefore, more flexible to perform system identification capturing the temporal behavior.
- 2) Using splines to characterize the curves with smooth functions, which leads to flexible system identification.
- 3) Inclusion of the peak discharging current of the battery when estimating SoC, allowing for a more comprehensive evaluation of battery performance.
- 4) Design of an MHE algorithm for SoC estimation from a fractional-order model, which provides an effective method for handling poor initial estimation and constraints on the battery model.

This brief is structured as follows: Section II presents the preliminary information. Section III contains the battery model and its peak discharging current. Section IV proposes the system identification. Section V details the MHE for the battery model. Section VI presents the numerical results. Finally, Section VII concludes the remarks of the brief.

II. PRELIMINARY

Our method relies on fractional-order calculus. In the following, we summarize its main results we will use in the brief. Fractional-order calculus extends the derivatives to an arbitrary (possibly fractional) order (e.g., Riemann–Liouville, Caputo, or Grünwald–Letnikov [29]). Hereafter, at time t , we consider the Grünwald–Letnikov definition with the α derivative of signal $u^t \in \mathbb{R}$ that can be defined as follows:

$$\mathcal{D}_\delta^\alpha u^t = \lim_{h \rightarrow 0} \frac{1}{h^\alpha} \sum_{k=0}^{\infty} \frac{(-1)^k \Gamma(\alpha + 1)}{\Gamma(k + 1) \Gamma(\alpha - k + 1)} u^{t-k} \quad (1)$$

where $\Gamma(\cdot)$ is the Gamma function defined as $\Gamma(n) = \int_0^\infty x^{n-1} e^{-x} dx$. To discretize (1), the sampling time δ is

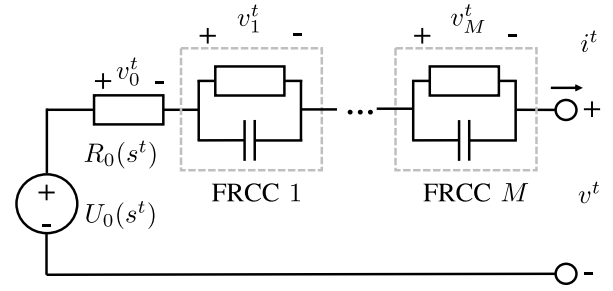


Fig. 1. Schematic of the battery model comprising OCV, a resistor, and M FRCCs.

considered to be fixed. Thus, the discrete Grünwald–Letnikov is defined as follows:

$$\mathcal{D}_\delta^\alpha u^t = \frac{1}{\delta^\alpha} \sum_{k=0}^{\infty} \frac{(-1)^k \Gamma(\alpha + 1)}{\Gamma(k + 1) \Gamma(\alpha - k + 1)} u^{t-k}. \quad (2)$$

III. BATTERY MODEL

A. Battery Circuitry

Let $v^t \in \mathbb{R}$ and $i^t \in \mathbb{R}$ denote the terminal voltage and current of the battery, respectively. To characterize the charge level of the battery, we define $s^t \in [0, 1]$ as the SoC of the battery at time $t \in \mathbb{N}$ that is calculated as follows:

$$s^{t+1} = s^t - \frac{\delta}{C} i^t + w_s^t \quad (3)$$

where $\delta > 0$ is the sampling time, and $C > 0$ is the capacity of the battery. In addition, $w_s^t \in \mathbb{R}$ stands for the disturbance affecting the SoC's dynamics at time t .

To model the battery, we use the circuitry that is illustrated in Fig. 1. The battery model consists of an OCV, a resistor, and multiple FRCCs. The OCV is denoted by $U_0(s^t) \geq 0$ and depends on the SoC of the battery s^t at time t . The resistive circuit has the SoC-dependent resistance $R_0(s^t) \geq 0$, and its voltage is computed by $v_0^t = R_0(s^t) i^t$. In addition, there are M FRCCs that are responsible for characterizing the transient response of the battery. Let $v_m^t \in \mathbb{R}$ and $i_m^t \in \mathbb{R}$ denote the voltage and the current of $m \in \{1, \dots, M\}$ FRCC, respectively. The evolution of voltage and current across the FRCC m is described by

$$\begin{aligned} i_m^t + \tau_m \mathcal{D}_\delta^{\alpha_m} i_m^t &= i^t \\ v_m^t &= R_m(s^t) i_m^t \end{aligned} \quad (4)$$

where $0 < \alpha_m < 2$ is the order of the derivative, and $\tau_m > 0$ is the time constant of FRCC m . In addition, $R_m(s^t) \geq 0$ stands for the resistance of FRCC m , and $\mathcal{D}_\delta^{\alpha_m} i_m^t$ indicates the discrete Grünwald–Letnikov fractional-order derivative of $i_m^t \in \mathbb{R}$. Hereafter, we consider a truncation K of the discrete Grünwald–Letnikov fractional-order as

$$\mathcal{D}_\delta^{\alpha_m} i_m^t = \frac{1}{\delta^{\alpha_m}} \sum_{k=0}^K \gamma_{m,k} i_m^{t-k} + e_{m,K}^t \quad (5)$$

where $\gamma_{m,k} = ((-1)^k \Gamma(\alpha_m + 1)) / (\Gamma(k + 1) \Gamma(\alpha_m - k + 1))$ and $e_m^t = (1/\delta^{\alpha_m}) \sum_{k=K}^{\infty} \gamma_{m,k} i_m^{t-k}$. The error introduced by the

truncation is negligible for a sufficiently large $K \in \mathbb{N}$ since $|\gamma_{m,k}| \leq ((\alpha_m)^K / K!)$ [30]. Therefore, we can rewrite (4) as

$$i_m^t + \frac{\tau_m}{\delta \alpha_m} \sum_{k=0}^{K-1} \gamma_{m,k} i_m^{t-k} + \tau_m e_{m,K}^t = i^t. \quad (6)$$

Based on (3) and (4), the terminal voltage is obtained as

$$v^t = U_0(s^t) - R_0(s^t)i^t - \sum_{m=1}^M R_m(s^t)i_m^t + w_v^t \quad (7)$$

where w_v^t stands for the noise of the terminal voltage.

B. Cubic Spline

The battery model (7) depends on the functions $U_0(s^t)$, $R_0(s^t)$, and $R_m(s^t)$ that depend on the SoC. To characterize these functions, we use their interpolation via cubic spline with $N+1$ points to assure continuity for the first and second derivatives [31], [32]. Let us consider partitioning the interval $[0, 1]$ into $N \in \mathbb{N}$ equally sized intervals by $x_n = n/N$ for $n = 0, \dots, N$. Then, for $s^t \in [x_n, x_{n+1}]$, we have

$$\begin{aligned} U_0(s^t) &= h_n^U P(N(s^t - x_n)) + h_{n+1}^U P(N(x_{n+1} - s^t)) \\ &\quad + y_n^U (N(s^t - x_n)) + y_{n+1}^U (N(x_{n+1} - s^t)) \\ R_0(s^t) &= h_n^0 P(N(s^t - x_n)) + h_{n+1}^0 P(N(x_{n+1} - s^t)) \\ &\quad + y_n^0 (N(s^t - x_n)) + y_{n+1}^0 (N(x_{n+1} - s^t)) \\ R_m(s^t) &= h_n^m P(N(s^t - x_n)) + h_{n+1}^m P(N(x_{n+1} - s^t)) \\ &\quad + y_n^m (N(s^t - x_n)) + y_{n+1}^m (N(x_{n+1} - s^t)) \end{aligned} \quad (8)$$

where $P(x) = (1/6)(x^3 - x)$. For $n = 0, \dots, N$, it follows that y_n^U , y_n^0 , and y_n^m are the values of the functions at $s^t = x_n$. Similarly, for $n = 0, \dots, N$, we have h_n^U , h_n^0 , and h_n^m parameters whose zero value indicates that the second derivative of the function is zero at $s^t = x_n$. Since $U_0(s^t)$, $R_0(s^t)$, and $R_m(s^t)$ are nonnegative, we have

$$y_n^U \geq 0, \quad y_n^0 \geq 0, \quad y_n^m \geq 0 \quad (9)$$

for $n = 0, \dots, N$ and $m = 1, \dots, M$. To ensure continuity in the first derivative, the following constraints must hold:

$$\begin{aligned} 0.5h_{n-1}^U + 2h_n^U + 0.5h_{n+1}^U &= 3(y_{n-1}^U - 2y_n^U + y_{n+1}^U) \\ 0.5h_{n-1}^0 + 2h_n^0 + 0.5h_{n+1}^0 &= 3(y_{n-1}^0 - 2y_n^0 + y_{n+1}^0) \\ 0.5h_{n-1}^m + 2h_n^m + 0.5h_{n+1}^m &= 3(y_{n-1}^m - 2y_n^m + y_{n+1}^m) \end{aligned} \quad (10)$$

for $n = 1, \dots, N-1$. For the boundary conditions (i.e., $n \in \{0, N\}$), we can assume that

$$h_0^U = h_N^U = h_0^0 = h_N^0 = h_0^m = h_N^m = 0. \quad (11)$$

Intuitively, the condition (11) implies that $U_0(s^t)$, $R_0(s^t)$, and $R_m(s^t)$ have more linear traits on the boundaries.

C. Peak Discharging Current

In this section, we delve into the examination of the battery's peak discharging current, a critical factor in governing the mobile robot's operations and orchestrating their tasks during low-battery scenarios. Every battery has a threshold for the

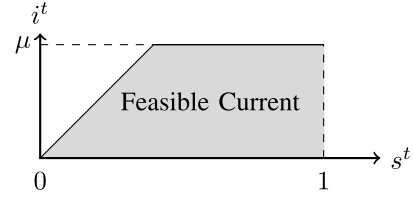


Fig. 2. Peak discharging current.

maximum power it can deliver, and this constraint plays a pivotal role in overseeing the battery of mobile robots and strategizing their missions. Moreover, when estimating the SoC, the peak discharging current defines a viable range beyond which achieving specific SoC values becomes unattainable. It is imperative that the estimated SoC values adhere to the constraints associated with the peak discharging current. The peak discharging current depends on the SoC [27]. Specifically, at a lower charge, it has a linear dependency

$$i^t \leq \gamma s^t \quad (12)$$

where $\gamma > 0$. Furthermore, the current does not exceed the constant μ , i.e., $i^t \leq \mu$. Fig. 2 depicts the feasible region for the terminal current.

IV. SYSTEM IDENTIFICATION

Given the battery model, this section describes the model's cubic splines to meet the battery's voltage and current data. To this end, we use a dataset from the terminal voltage and current for system identification. We aim to identify the parameters of the cubic splines regarding OCV, the resistor, and FRCCs' resistor, i.e., y_n^U , y_n^0 , y_n^m , h_n^U , h_n^0 , and h_n^m . In addition, we determine the parameters of the peak discharging current with the data.

On our dataset, $v^{t,q}$ and $i^{t,q}$ are available for trial $q = 1, \dots, Q$ at $t = 1, \dots, T_q$. Given α_m and τ_m , we can calculate $i_m^{t,q}$ time series for $m = 1, \dots, M$ via (6). The trials start from the full-charge situation, and based on the initial SoC of each trial, we can calculate $s^{t,q}$ via Coulomb counting from (3). Let z^{SI} stand for the vector that concatenates the variables y_n^U , y_n^0 , y_n^m , h_n^U , h_n^0 , and h_n^m , for $n = 0, \dots, N$ and $m = 1, \dots, M$. Given the data from $v^{t,q}$, $i^{t,q}$, and $s^{t,q}$, the following optimization to obtain the cubic spline parameters:

$$\begin{aligned} \min_{z^{\text{SI}}} \quad & \sum_{q=1}^Q \sum_{t=1}^{T_q} \left\| v^{t,q} - U_0(s^{t,q}) - R_0(s^{t,q})i^{t,q} + \sum_{m=1}^M R_m(s^{t,q})i_m^{t,q} \right\|^2 \\ & + \sum_{n=0}^N (\lambda^U |h_n^U| + \lambda^0 |h_n^0| + \lambda^m |h_n^m|) \\ \text{s.t.} \quad & (8), (9), (10), \text{ and } (11) \text{ for } n = 0, \dots, N \\ & m = 1, \dots, M, \quad \text{and } q = 1, \dots, Q. \end{aligned} \quad (13)$$

where λ^U , λ^0 , and λ^m are the hyperparameters. The term $\sum_{n=0}^N (\lambda^U |h_n^U| + \lambda^0 |h_n^0| + \lambda^m |h_n^m|)$ has a regularization role for the system identification to promote a lower second derivative. Specifically, the absolute value may lead some of h_n^U , h_n^0 , and h_n^m to be zero, which shows the tendency of (13) to obtain the linear curves for $U_0(s^t)$, $R_0(s^t)$, and $R_m(s^t)$ at each point.

Algorithm 1 System Identification for Modeling Battery**Inputs**

Time series of $v^{t,q}$ and $i^{t,q}$ for $q = 1, \dots, Q$ at $t = 1, \dots, T_q$
 α_m and τ_m for $m = 1, \dots, M$
 λ^U , λ^0 , and λ^m

SoC

Calculate $s^{t,q}$ from (3) for each trial $q = 1, \dots, Q$ at $t = 1, \dots, T_q$

FRCC

Calculate $i_m^{t,q}$ from (4) and (5) for $m = 1, \dots, M$ and $q = 1, \dots, Q$ at $t = 1, \dots, T_q$

System Identification

Solve the optimization problem (13)

Based on (8), $U_0(s^{t,q})$, $R_0(s^{t,q})$, and $R_m(s^{t,q})$ have a linear dependency on the optimization parameters. Therefore, the cost function in (13) is convex with respect to the optimization parameters. Moreover, (9)–(11) are linear constraints with respect to the optimization parameters. Therefore, (13) is a convex optimization and has a unique solution. Algorithm 1 provides the procedure for system identification in (13).

The constraint in (12) shows the limitation on the terminal current. To determine μ and γ , we assume a dataset containing adequate situations with extracting peak current for the whole range of SoC. Thus, they can be computed by $\mu = \max i^{t,q}$ and $\gamma = \max(i^{t,q}/s^{t,q})$, with $q = 1, \dots, Q$ and $t = 1, \dots, T_q$.

V. MOVING HORIZON ESTIMATION

The battery model has hidden states, such as the SoC or the FRCCs' current, which cannot be measured directly. Given an identified battery model, we design a state estimator from the observed data of terminal voltage and current via MHE.

Let us assume the time series of the terminal voltage (v^t) and terminal current (i^t) are available. To this end, we use MHE to estimate states based on a sequence of H past measurements. Let us define $H^t = \min\{H, t\}$ to handle the MHE at the initial stage where the available samples are less than H . Suppose $v^{(t-H^t):t} = [v^{t-H^t}, \dots, v^t]^\top$ and $i^{(t-H^t):t} = [i^{t-H^t}, \dots, i^t]^\top$ be the observed sequence of terminal voltage and current, respectively. In addition, suppose that \hat{s}^{t-H^t} and $\hat{i}_m^{t-H^t}$ are the available estimation of s^{t-H^t} and $i_m^{t-H^t}$, respectively. Let us define $\tilde{s}^{(t-H^t):t} = [\tilde{s}^{t-H^t}, \dots, \tilde{s}^t]^\top$ and $\tilde{i}_m^{(t-H^t):t} = [\tilde{i}_m^0, \dots, \tilde{i}_m^{H^t+1}]^\top$ as optimization variables corresponding to a sequence of s^t and i_m^t , respectively.

Based on the dynamics of the SoC in (3), we have the following constraints:

$$\begin{aligned} \tilde{s}^{t'+1} &= \tilde{s}^{t'} - \frac{\delta}{C} i^{t'} + \tilde{w}_s^{t'}, \quad \text{for } t - H^t \leq t' \leq t - 1 \\ 0 &\leq \tilde{s}^{t'} \leq 1, \quad i^{t'} \leq \gamma \tilde{s}^{t'}, \quad \text{for } t - H^t \leq t' \leq t. \end{aligned} \quad (14)$$

Let us denote $\tilde{w}_s^{(t-H^t):(t-1)} = [\tilde{w}_s^{t-H^t}, \dots, \tilde{w}_s^{t-1}]^\top$. Moreover, according to (6), we have the following constraints:

$$\tilde{i}_m^{t'} + \tau_m \sum_{k=0}^{t-H^t-t'} \gamma_{m,k} \tilde{i}_m^{t'-k} + \tau_m \tilde{e}_m^{t'} = i^{t'} \quad (15)$$

for $t - H^t \leq t' \leq t$. Let us denote $\tilde{e}_m^{(t-H^t):t} = [\tilde{e}_m^{t-H^t}, \dots, \tilde{e}_m^t]^\top$. Note that (15) uses different truncations for different t' because we only use the terminal current's data for the estimation in the interval $t - H^t$ to t .

Based on (7), for the voltage measurements, we have the following constraint:

$$v^{t'} = U_0(\tilde{s}^{t'}) - R_0(\tilde{s}^{t'}) i^{t'} - \sum_{m=1}^M R_m(\tilde{s}^{t'}) \tilde{i}_m^{t'} + \tilde{w}_v^{t'} \quad (16)$$

for $t - H \leq t' \leq t$. Let us denote $\tilde{w}_v^{(t-H^t):t} = [\tilde{w}_v^{t-H^t}, \dots, \tilde{w}_v^t]^\top$. It would be difficult to use (16) as constraints since it is not linear with respect to $\tilde{s}^{t'}$. Therefore, we linearize (16) around $s = \hat{s}^{t-H^t}$ as

$$v^{t'} = u_0 + l_0 \tilde{s}^{t'} - r_0 i^{t'} - \sum_{m=1}^M r_m \tilde{i}_m^{t'} + \tilde{w}_v^{t'} \quad (17)$$

where

$$\begin{aligned} u_0 &= U_0(\hat{s}^{t-H^t}), \quad l_0 = \frac{\partial U_0}{\partial s}(\hat{s}^{t-H^t}), \quad \text{and} \\ r_0 &= R_0(\hat{s}^{t-H^t}), \quad r_m = R_m(\hat{s}^{t-H^t}). \end{aligned} \quad (18)$$

Let $z^{\text{MHE},t}$ stand for the vector that concatenates the variables $\tilde{s}^{(t-H^t):t}$, $\tilde{i}_m^{(t-H^t):(t-1)}$, $\tilde{w}_s^{(t-H^t):(t-1)}$, $\tilde{w}_v^{(t-H^t):t}$, and $\tilde{e}_m^{(t-H^t):t}$ for $m = 1, \dots, M$. By defining the constraints, the MHE is formulated as follows:

$$\begin{aligned} \min_{z^{\text{MHE},t}} \quad & p_s \|\tilde{s}^{t-H^t} - \hat{s}^{t-H^t}\|^2 + \sum_{m=1}^M p_{i,m} \|\tilde{i}_m^{t-H^t} - \hat{i}_m^{t-H^t}\|^2 \\ & + \|\tilde{w}_s^{(t-H^t):(t-1)}\|_{P_s}^2 + \|\tilde{w}_v^{(t-H^t):t}\|_{P_v}^2 \\ & + \sum_{m=1}^M \|\tilde{e}_m^{(t-H^t):t}\|_{P_{i,m}}^2 \\ \text{s.t.} \quad & (14), (15), \text{ and } (17) \text{ for } m = 1, \dots, M \end{aligned} \quad (19)$$

where p_s and $p_{i,m}$ are the weights of the initial estimation terms that lead \tilde{s}^{t-H^t} and $\tilde{i}_m^{t-H^t}$ to be obtained close to the last estimations (i.e., \hat{s}^{t-H^t} and $\hat{i}_m^{t-H^t}$) at the beginning of the interval. The matrices P_s , P_v , and $P_{i,m}$ are the weights of different cost function terms.

Algorithm 2 shows the procedure of MHE. The MHE is initiated with the initial estimates \hat{s}^0 and \hat{i}_m^0 for $m = 1, \dots, M$. At time t , the optimal values of $\tilde{s}^{(t-H^t):t}$ and $\tilde{i}_m^{(t-H^t):t}$ are calculated based on the last estimations \hat{s}^{t-H^t} and $\hat{i}_m^{t-H^t}$ for $m = 1, \dots, M$ on the horizon $(t - H^t)$ to t . Afterward, \hat{s}^{t-H^t+1} and $\hat{i}_m^{t-H^t+1}$ are updated with the optimal values of the corresponding elements $z^{\text{MHE},t}$ from the optimization (19).

An advantage of MHE is that it can account for constraints in the estimation problem. There are two types of inequality constraints in our proposed solution (see Algorithm 2): i) the SoC range and ii) the peak discharging current. Based on the SoC range and the nature of the battery, it is impossible to violate these constraints, e.g., SoC more than 1 or high current in low-battery mode. The constraints in MHE are responsible for forcing the estimation to be in the feasible region.

Algorithm 2 MHE for Battery Model at Time t **Inputs**Estimation horizon H $p_s, p_{i,m}, P_s, P_v$, and $P_{i,m}$ for $m = 1, \dots, M$ The initial estimations \hat{s}^0 and \hat{i}_m^0 for $m = 1, \dots, M$ **For** time $t \geq 0$

$$H^t = \min\{H, t\}$$

$$v^{(t-H^t):t} = [v^{t-H^t}, \dots, v^t]^\top$$

$$i^{(t-H^t):t} = [i^{t-H^t}, \dots, i^t]^\top$$

LinearizationCalculate u_0, l_0, r_0 , and r_m by (18) for $m = 1, \dots, M$ **MHE**

Solve the optimization problem (19)

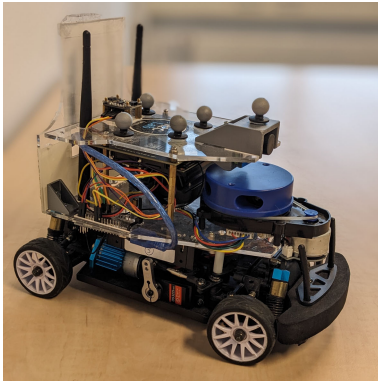
Update \hat{s}^{t-H^t+1} and $\hat{i}_m^{t-H^t+1}$ for $m = 1, \dots, M$ 

Fig. 3. Mobile robot.

VI. NUMERICAL RESULTS

A. Mobile Robot Data

To evaluate the methodology, we apply the algorithms to the battery data of a mobile robot in five trials. Fig. 3 shows the mobile robot used for the experiments. For each trial, the robot starts in a fully charged state. Then, it moves and stops frequently to deplete the battery. The robot's battery is a two-cell rechargeable polymer lithium-ion battery with a 550-mAh capacity with a usable voltage range of 3.2–4.2 V per cell. The trials are divided into two sets of training (four trials) and testing (one trial) results. Fig. 4 shows the terminal voltage and current time series of the battery for the training data. Note that the terminal voltage and current have many sharp peaks and drops due to the route that the mobile robot follows. In addition, the current drops at the end of the experiment because of the limitations on low-battery mode.

B. System Identification

For system identification, we use the training data, and we calculate the SoC via Coulomb counting from (3) and using the assumption that the trial starts from fully charged mode. For system identification, we consider a battery model with one FRCC with $\alpha_1 = 1.2$ and $\tau_1 = 0.05$ s. We considered $N = 21$ points regarding $U_0(s^t)$, $R_0(s^t)$, and $R_1(s^t)$. The

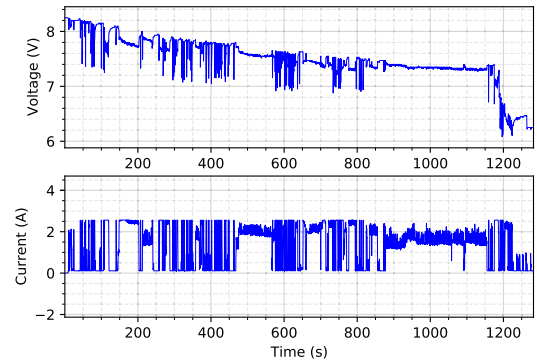


Fig. 4. Voltage and current time series for a trial.

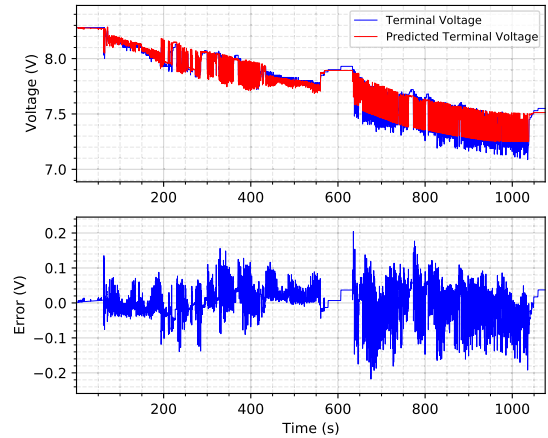


Fig. 5. Terminal voltage prediction and prediction error on testing data.

hyperparameters λ^U , λ^0 , and λ^1 are considered to be 15, 150, and 100, respectively. The truncation sample size for fractional-order calculation is considered as $K = 10$.

The parameters of the battery model are determined using Algorithm 1. To evaluate the model, we use cross-validation on the testing data. Fig. 5 shows the terminal voltage, its prediction, and its error. The predicted voltage follows the trend of the real terminal voltage, and the model follows the battery's behavior well. The prediction error does not exceed 0.25 V (35% of the terminal voltage). The prediction percent error (PE^t) at time t is defined as $PE^t = 100(|v^t - \hat{v}^t|/v^t)$ where v^t and \hat{v}^t are the real and predicted voltages, respectively. Our model's average percent error (the percentage of prediction error to the real value) is approximately 0.53%. However, it might be possible to get less error upon fine-tuning some of the parameters. In addition, the parameters μ and γ are equal to 2.6 and 11.9 A, respectively.

Fig. 6 shows the OCV determined by our proposed method as described in Section IV. The system identification smoothly calculates the OCV curve. Although there are $N = 21$ points for interpolation of the curve, the curve stays smooth as much as possible because of the regularization term $\sum_{n=0}^N \lambda^U |h_n^U|$. This regularization decreases the curvature of the splines at each interpolation point so that the curve remains linear as far as it is possible. The OCV drops when SoC is close to 0.28. In addition, we have less change in OCV in the middle range than in the high range of SoC.

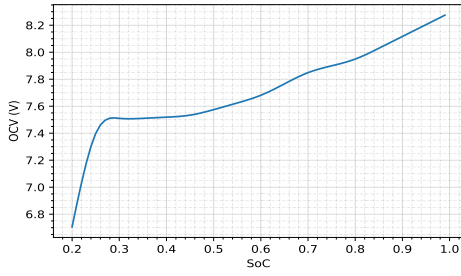


Fig. 6. OCV curve obtained by the system identification.

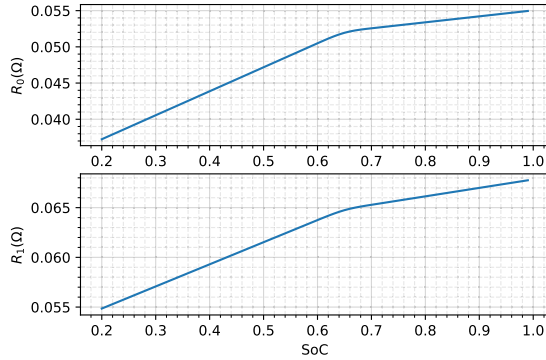


Fig. 7. Resistance curve for resistive circuit and FRCC obtained from system identification.

Fig. 7 displays the resistance curves for the resistor and the FRCC. Similar to the OCV curve, these curves are obtained smoothly with less fluctuation because of the regularization terms in system identification. Contrary to the pulse-based experiments for determining resistance parameters as in [16] and [17], our method uses data-driven techniques that leverage natural terminal current fluctuations. This strategy proves especially beneficial for mobile robots, given the integration of the battery with diverse circuits, such as motor drivers. Using direct observations, our method streamlines the estimation process, enhancing its relevance to the practical operation of mobile robots. Moreover, this approach facilitates the scalability and deployability of mobile robots in real-world environments, underscoring its practical advantages.

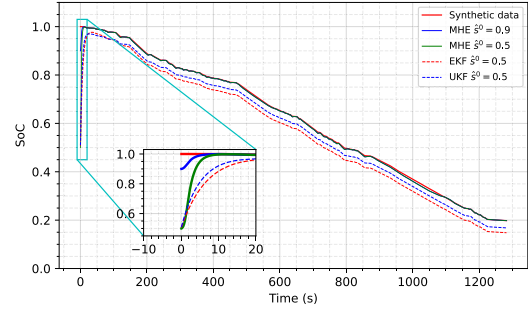
Table I depicts the performance of the modeling with respect to the fractional-order of the derivative via average percent error. The average percent error has its lowest value on $\alpha_1 = 1.2$. Specially, when $\alpha_1 = 1$ (integer order model), we have higher errors than with $\alpha_1 = 1.2$, which shows the advantage of using fractional-order models. In addition, we repeated the simulations for two FRCCs, and as shown in Table I, the fractional-order systems can perform better than multiple integer order elements for describing the temporal behavior.

C. Moving Horizon Estimation

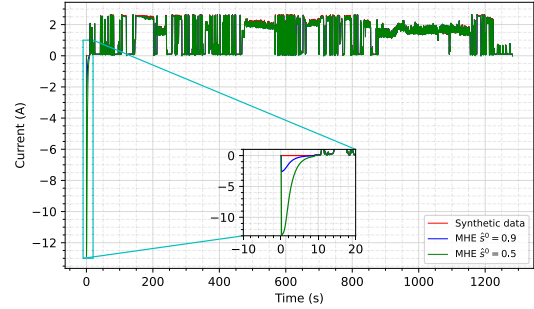
Assuming that the terminal current and voltage are available, MHE exploits the identified battery model to estimate the SoC and the current of the FRCC. We consider $H = 20$ for the horizon of the MHE. The hyperparameters are considered as follows: $p_s = 1000$, $p_{i,1} = 1000$, $P_s = 100\,000I_H$, $P_v = I_H$, and $P_{i,1} = 0.1I_H$ where I_H is identity matrix with size $H \times H$.

TABLE I
AVERAGE PERCENT ERROR OF THE SYSTEM IDENTIFICATION WITH
RESPECT TO THE ORDER OF FRACTIONAL DERIVATIVE

	Single FRCC	Double FRCCs	
		$\alpha_2 = 1$	$\alpha_2 = 1.1$
$\alpha_1 = 0.9$	1.23%	1.92%	1.57%
$\alpha_1 = 1.0$	0.91%	1.21%	1.03%
$\alpha_1 = 1.1$	0.62%	0.87%	0.71%
$\alpha_1 = 1.2$	0.53%	0.63%	0.58%
$\alpha_1 = 1.3$	0.57%	0.68%	0.61%



(a) Estimation of SoC.



(b) Estimation of the FRCC's current.

Fig. 8. MHE from the synthetic data for $\bar{s}^0 = 0.9$ and $\bar{s}^0 = 0.5$ cases. (a) EKF and UKF estimation results (implemented based on [33]) from the synthetic data with initial value $\bar{s}^0 = 0.5$. (a) Estimation of SoC. (b) Estimation of the FRCC's current.

The truncation sample size is considered to be $K = 10$ for the discretized fractional-order dynamics.

As a ground truth, to validate the MHE, we used synthetic data that are artificially generated by simulation. To do so, we extract the current time series of training data from the model and set 1 for the initial SoC. The synthetic data contain the simulation values for the states (SoC and the current of FRCC) that can be compared with the estimated states. For MHE, we consider two different values of the initial SoC of the estimation: $\bar{s}^0 = 0.9$, $\bar{s}^0 = 0.5$, EKF (for $\bar{s}^0 = 0.5$), and UKF (for $\bar{s}^0 = 0.5$). Fig. 8(a) shows the synthetic data and the results of MHE for the two aforementioned cases. In particular, the estimates of SoC converge to the synthetic SoC. In contrast to EKF and UKF, MHE converges quickly to the synthetic SoC regardless of different initial estimations. In addition, Table II shows comparison of the sensitivity of the methods to initial estimation. MHE has less error compared with the other methods to compensate for poor initial estimation. That provides evidence of an advantage of MHE in coping with a poor initial value of the SoC.

TABLE II
AVERAGE ABSOLUTE ERROR OF THE ESTIMATION METHODS WITH
RESPECT TO THE INITIAL ESTIMATED SoC

\hat{s}^0	MHE	EKF	UKF
0.9	0.0023	0.0028	0.0024
0.8	0.0025	0.0057	0.0048
0.7	0.0028	0.0142	0.0115
0.6	0.0032	0.0356	0.0223
0.5	0.0035	0.0486	0.0314

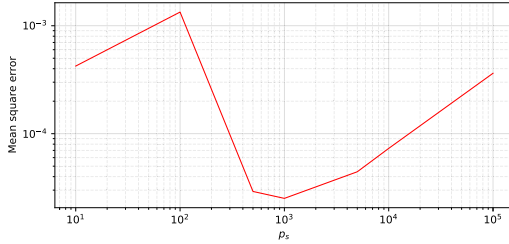


Fig. 9. Mean square error of MHE with respect to p_s .

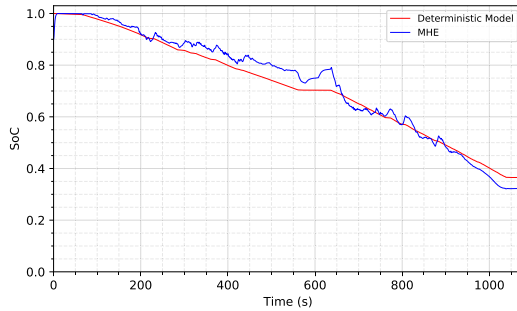


Fig. 10. Estimation of SoC for MHE and Coulomb counting (the deterministic battery model) from test data.

Fig. 8(b) depicts the estimation results for the current of the FRCC from the synthetic data for the two aforementioned cases. Although the initial condition for the FRCC's current is the same, the estimations have some errors in the initial stage of the trajectory. The error happens in light of the poor initial condition of the SoC. However, the MHE compensates for the error with almost 8 s.

The quality of MHE depends on the parameters in optimization (19). Fig. 9 displays the mean square error of MHE and synthetic data with respect to p_s . p_s determines how much MHE relies on the previous estimation for the next estimation. The less the p_s , the noisier the results are obtained because MHE tends to estimate regardless of the previous estimations. Note that big values of p_s make MHE dependent on previous estimations, leading to slow estimation.

To validate the MHE on real data, we feed MHE with the test data and compare the results with Coulomb counting. Coulomb counting results can be interpreted as the deterministic battery model, i.e., by considering (3) with zero noise in SoC. Note that Coulomb counting neglects the stochasticity of the battery and is not a ground truth for estimation. The SoC's initial value is set at 0.9. Fig. 10 shows the estimation of SoC with MHE and Coulomb counting. Note that the trajectories follow each other with an average and maximum absolute error of 0.04 and 0.08, respectively (after the transient stage).

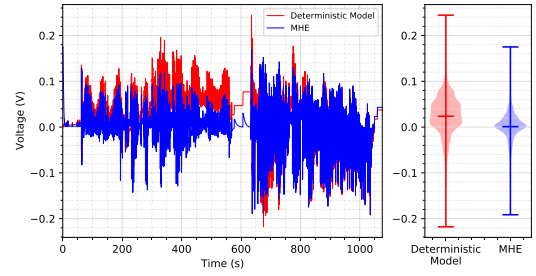


Fig. 11. Estimation of the terminal voltage error and its distributions for MHE and Coulomb counting (the deterministic battery model) from test data. The ticks on the violin plot show the minimum, maximum, and mean of the errors.

The difference between these two trajectories is due to the stochastic nature of the battery, system identification error, and MHE's error.

Fig. 11 depicts the estimation error of the measured voltage for MHE and the deterministic model. The errors are calculated by subtracting the terminal voltage of the real data from the estimated voltages calculated by evaluating the estimated states in (7). Fig. 11 shows the errors' distributions, and in particular, note that MHE is closer to zero.

VII. CONCLUSION

This research brief proposes a novel methodology for system identification and state estimation of batteries in mobile robots. Our approach uses fractional-order components for increased temporal flexibility and cubic spline interpolation to obtain smooth curves for OCV and resistors. We also consider the limitation on peak discharging voltage to achieve a well-defined optimization problem for the MHE algorithm used for SoC estimation. Our methodology is validated through numerical results obtained from voltage and current data of a mobile robot, demonstrating the effectiveness of the system identification and MHE in accurately estimating the SoC even with poor initial values.

Future research will aim to enhance our framework by incorporating considerations of the battery's state of health (e.g., aging effects). Specifically, we believe it would be worth exploring a pretrained model using our system identification framework, followed by iterative updates using recursive least-squares techniques to account for state of health and/or aging dynamics. Furthermore, we intend to conduct empirical research to assess the impact of temperature on battery performance, recognizing its significant influence on modifying battery parameters.

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