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Swarm Evolutionary Technique for Dynamic Response Modeling of Lithium Cell Using Updated Multi-Objective Ant-Lion Optimizer

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Abstract:
In this research paper, a swarm evolutionary modeling technique called the Updated Multi-Objective Ant-Lion Optimizer (UMO-ALO) is applied to the modeling of Open Circuit Voltage (OCV) state-of-charge (SOC) of Lithium-ion cells with cathode-anode composition (LiMnO2/Li4TiO). The model approximates the battery SOC by considering several battery cell internal physical parameters and a linear fitness function governed by two objectives involving the charge and discharge response of the battery cell. Bound limited coefficients of the physical parameters are used in the optimization process. The UMO-ALO uses a special update procedure to reduce the computational run-time of standard MO-ALO and hence speeds up the generic optimizer. Simulations were performed using a very small real laboratory data obtained from the relevant field studies and for different trial-run configurations of UMO-ALO. The results from these simulations show very good fitness response close to zero-margins for both trial-run configurations.

Keywords: Cathode-anode composition, Discharge response, Lithium-ion cells, Multi-objective Optimizer, Open-circuit-voltage, State-of-charge.

I. Introduction

Coronaviruses The field of direct current (dc) energy storage cells is a thriving one considering the vast number of applications that requires such form of electricity and the relatively simple/flexible storage requirement compared to the equivalent alternating current (ac) energy storage systems. Some of the key requirements/or benefits of dc cells are durability, high ampere capacity, portability, temperate operability, stationary operation, longevity (low self-discharge), low cost, and especially operationally safety (Stan et al., 2014). Popular among the dc energy storage systems are the class of cells referred to as the Lead acid cells. While these cells are popular due to low initial cost but there are not very efficient and are characterized by short life spans and safety issues (Superlib, 2012).

In this regard, the Lithium-ion cells are currently gaining widespread acceptance and used as a viable source of dc energy storage for many purposes particularly in the vehicle applications sector.

Unfortunately, the long-term benefits of Lithium-ion cells may be inhibited by certain techno-economic factors during actual production modeling necessitating a more thorough evaluation of production processes. In part, these factors may be largely attributed to the wide variations in power densities and in turn for a variety of specified battery chemistries making it difficult to describe cell output voltage states using simple process models (Burke & Miller, 2009). As having good models is essential for gaining insight into battery cell operation and efficient evaluations prior to production and operational service, current attempts at improving the performance of Lithium-ion cell design processes resort to the use of high-level data-driven model simulations including but not limited to standard regressors, neural networks and more recently evolutionary programming systems (Meng et al., 2018; Dong et al., 2015; Bruce et al., 2017). These more advanced model simulator techniques attempt to describe the cell output voltage state with respect to standard electro-physical parameters such as the cell charge current, cell capacity, specific capacity and energy in a data-driven context. However, the solutions in such models may result in sub-optimality, loss of diversity and/or inadequate (complicated) models. In addition, fitness function models exploited in such solutions are usually very constrained to single objectives lacking in diversity and distributed processing.

In this research paper, a more powerful and novel data-driven swarm evolutionary approach called the Updated Multi-Objective Ant Lion Optimizer (UMO-ALO) for speeding-up and further enhancing the model optimization of the Lithium-ion cell is proposed. The novelty of the proposed UMO-ALO lies in the employment of a unique update process that reduces the computational run-time of standard MO-ALO and in addition exploits a linear fitness function model thereby enhancing and greatly simplifying the modeling process. It also uses a very small dataset making it more difficult for the optimizer to solve.

In the subsequent section of Section 2, a review of existing studies in the state-of-the-art for Lithium-ion modeling is presented. In the Section 3, the methodology employed including a first-order transient battery model and the proposed UMO-ALO methodology is described and its motivational parameters clearly defined. Section 4 presents

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simulation results and in Section 5 we discuss the results and present our conclusions.

II. RELATED RESEARCHES

Lithium-ion research is an ongoing activity with a great number of researches being churned out on a yearly basis. In the field of modeling and optimization, the research activities primarily border on how to optimize the battery Open Circuit Voltage (OCV) charge and discharge states considering the battery cell output voltage and internal cell chemistries or parameters.

Some existing researches using simple battery models with electrochemical and thermal models can be found in (Benger et al., 2009) and in (Huria et al., 2012) where iterative discharge profiling based on single-cell thermal model was adopted. In (Schönberger, 2013), the author used the current and temperature dependent factors for battery state of discharge modeling. Also, in (Einhorn et al., 2010a), simple interpolation techniques were employed for battery cell state of charge (SOC) modeling, and in (Vyroubal et al., 2014) an exponential-time zone model was proposed for modeling battery charge/discharge cycles and simulated in the MATLAB-SIMULINK program.

Furthermore, attempts at optimization approaches have been investigated in (Einhorn et al., 2010b) where a GPS Hooke-Jeeves Optimizer was applied to the modeling of battery SOC considering an integral-square of the difference between estimated and actual battery cell voltage. (Castanho et al., 2022) proposed the use of a Multiple Linear Regression (MLR) approach for battery cell SOC estimation in which the free coefficients of the MLR are trained by a Particle Swarm Optimizer (PSO).

While the aforementioned techniques have been successfully applied to the modeling of a variety of cell types, the problem still persist as to how best they represent real battery operation in a real-world context. Thus, the current approaches should emphasize data-driven solutions as SOC parameters can be analyzed and measured particularly with very small datasets.

In this research paper, an approach inspired by the intelligent behavior of the winged insects called ant-lions is exploited in a multi-objective way for battery SOC modeling using very small data obtained from real laboratory measurements.

III. MATERIALS AND METHODS

In this section, the approach for modeling battery SOC is presented. The approach considers the first-order transient response model and small-scale laboratory results for the $LiMnO_2/Li_4TiO$ cell as described in (Lin et al., 2012). It also presents details of the UMO-ALO technique proposed in this research paper.

First-Order Transient Response (FORT) Model

In order to describe the OCV of a battery cell, the First-Order Transient Response (FOTR) model (Lin et al., 2012) is employed.

The model describes the OCV as a function of the battery cell's state-of-charge (SOC) and in addition the variation of R0, R1, and C1 with the SOC where:

R0 = the cell internal ohmic resistance, mΩ

R1 = the cell polarized resistance, mΩ and

C1 = the cell polarized capacitance μF.

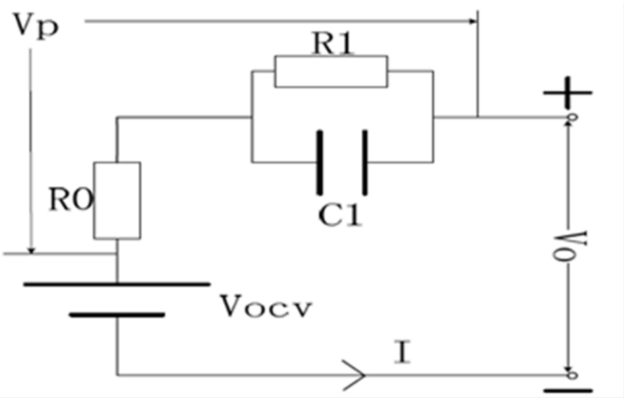

Figure 1: FOTR Model of a Battery Cell (Source: Lin et al., 2012).

In Figure 1 is shown the schematic of the FOTR model as proposed in (Lin et al., 2012). The variables (cell parameters) R0, R1, and C1 are typically measured at a given SOC in a laboratory-type environment and further estimated using a model-fitting program for calibration purposes. The measured values can also be used as inputs to an optimization program to build correlations with SOC as target in the model-fitting context.

To build a charge and/or discharge step-pulse during the estimation of the aforementioned variables, a time constant is computed as:

$$\tau = R1 \times C1 \qquad (1)$$

Updated Multi-objective Ant-lion Optimizer

The Updated Multi-objective Ant-lion Optimizer (UMO-ALO) is an attempt at developing a more time responsive optimization process. The Ant Lion Optimizer will be discussed here and then the technique of updates to improve speed is presented next.

Ant Lion Optimizer

Ant-Lion Optimizer (ALO) is a data-driven metaheuristic inspired by the intelligent random walk process of winged insects called ant-lions while they search for their prey (Mirjalili et al., 2017). The ALO borrows from the principles of dominance, fitness, coverage and pareto-optimality.

Fundamentally, the ALO comprise of 8 key phases:

- Random-walk phase
- Boundary conditioning phase
- Sliding ants mimic phase
- Entrapment phase

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- Ant-trap phase
- Ant-capture and pit reconstruction phase
- Elitist ants' storage phase
- Pareto-optimal and archival storage phase

The above phases are calculated using the computational model formulas as summarized in Table 1. Full details of the behavior of these models are provided in (Mirjalili et al., 2016).

Considering the case of a multi-objective solution process and any underlying boundary constrains,

$$f_{obj(1)} = \sum_{i}^{iter\_max} \left(\left| SOC_{actual(i)} - SOC_{estimated(i)} \right| \right) \quad (2)$$

$$f_{obj(2)} = \sum_{i}^{iter\_max} \left(\left| SODSCH_{actual(i)} - SODSCH_{estimated(i)} \right| \right) \quad (3)$$

Following a linear-curve fitting model, the estimated states of charge (SOC) and discharge (SODSCH) cycles are expressed as:

$$SOC_{estimated} = k_{c1}R0 + k_{c2}R1 + k_{c3}\tau + k_c \quad (4)$$

$$SOC_{estimated} = k_{c1}R0 + k_{c2}R1 + k_{c3}\tau + k_c \quad (5)$$

TABLE I COMPUTATIONAL MODELS OF THE ANT-LION OPTIMIZER

Phase id	Description	Model
1	Random-walk phase	$X(t) = \left[0, cumsum(2r(t_1) - 1), cumsum(2r(t_2) - 1), \ldots, cumsum(2r(t_n) - 1) \right]_{t=0:n}$ $r(t) = \begin{cases} 1, & if\ rand > 0.5 \\ 0, & otherwise \end{cases}$
2	Boundary conditioning phase	$X_i^t = \frac{(X_i^t - a_i) \times (u_i^t - l_i^t)}{b_i - a_i} + l_i^t$
3	Sliding ants mimic phase	$l^t = \frac{l^t}{I}$, $u^t = \frac{u^t}{I}$, $I = I + 10^w \frac{t}{T}$
4	Entrapment phase	$l_i^t = Antlion_j^t + l_i^t$ $u_i^t = Antlion_j^t + u_i^t$
5	Ant-trap phase	$Ant_i^t = \begin{cases} i, & [0, cumsum(w)]_{i=0:n} > r(t) \\ -1 \end{cases}$, Roulette-wheel n = length(w)
6	Ant-capture and pit reconstruction phase	$Antlion_j^t = Ant_i^t$ $if\left(f\left(Ant_i^t\right) > f\left(Antlion_j^t\right)\right)$
7	Elitist ants storage phase	$Ant_i^t = \frac{R_A^t + R_E^t}{2}$
8	Pareto-optimal and archival storage phase	$p_i = \frac{c}{N_i}$, Archive Improvement $p_i = \frac{N_i}{c}$, Archive Decongestion

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IV. Simulation Results

The results considering the internal battery cell parameters described earlier in Section 3 (sub-section 3.1) are presented in this section. The simulation data, UMO-ALO settings and the optimizer boundary conditions for generating the results are as provided in Tables 2, 3 and 4 respectively. The simulation uses a limited (very small) dataset which makes it especially more challenging for the algorithm to solve.

The simulations are performed in two parts; first part is conducted for 3 trial runs and at 100 iterations. The second part is conducted for only a single trial run at 5000 iterations.

TABLE 2: SIMULATION DATASET

SOC	Discharge			Charge		
	R0 (mΩ)	R1 (mΩ)	τ (sec)	R0 (mΩ)	R1 (mΩ)	τ (sec)
0.10	1.97	0.60	25	1.40	0.49	13
0.30	1.54	0.68	32	1.22	0.56	21
0.50	1.23	0.31	19	1.13	0.33	19
0.70	1.17	0.37	23	1.07	0.40	24
0.90	1.13	0.45	24	1.04	0.55	31

TABLE 3: UMO-ALO OPTIMIZER PARAMETERS

Parameter	Default Value
Maximum Iteration	100
Number of Search Agents	100
Maximum Storage Size of the Archive	100

TABLE 4: OPTIMIZER BOUNDARIES FOR DECISION VARIABLES

Optimizer Decision Variable	Min Value	Max Value
k_{c1}	0.002	5.0
k_{c2}	0.002	5.0
k_{c3}	0.002	5.0
k_{d1}	0.002	5.0
k_{d2}	0.002	5.0
k_{d3}	0.002	5.0
Kc	-0.002	0.1
Kd	-2.000	1.0

Battery SOC Results (100iterations)

The fitness response plots using default settings of the UMO-ALO (see Table 3) and considering the optimizer boundaries (Table 4) are as shown in Figure 2, Figure 3 and Figure 4 for the trial runs 1, 2 and 3 in that order. Also shown in Table 5 are the numerical results of the optimized decision variables (ODVs).

TABLE 5: OPTIMIZED DECISION VARIABLES (ODVS) AT 100ITERATIONS

Boundary Variable	Opt. Value (Trial 1)	Opt. Value (Trial 2)	Opt. Value (Trial 3)
k_{c1}	0.2303	0.0525	0.0539
k_{c2}	0.3277	1.3748	1.3950
k_{c3}	0.0150	0.0021	0.0025
k_{d1}	0.2078	1.0200	0.7411
k_{d2}	0.8729	1.0337	3.5828
k_{d3}	0.0021	0.0405	0.0021
kc	0.0137	0.0238	-0.0013
kd	0.2250	-1.6963	-1.5991

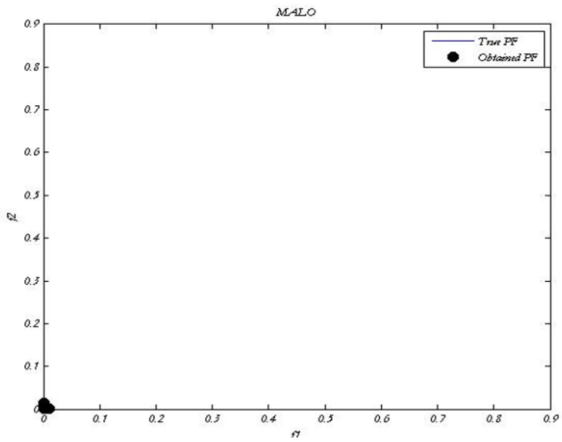

Figure 2: Fitness Response for Trial 1, Default-setting, and 100iterations.

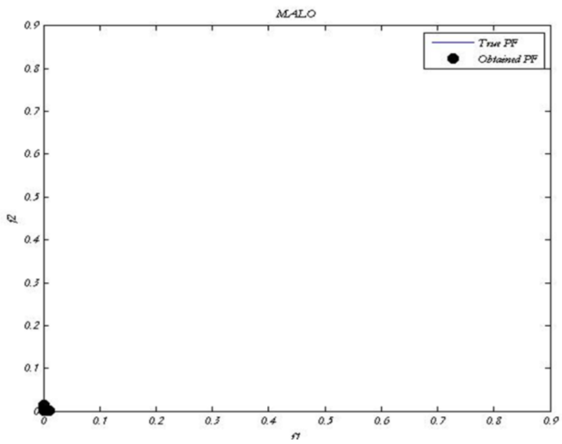

Figure 3: Fitness Response for Trial 2, Default-setting, and 100iterations.

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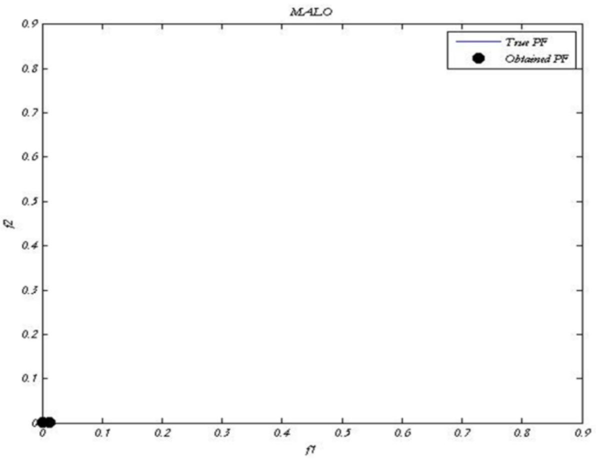

Figure 4: Fitness Response for Trial 3, Default-setting, 100iterations

Battery SOC Results (5000iterations)

In this part, the maximum number of iterations was increased from default setting of 100 to 5000 iterations to verify if there was any appreciable improvement in fitness response. The fitness response plot for this case is as shown in Figure 5. Also, the solved ODVs as a result of the fitting process of UMO-ALO are as shown in Table 6.

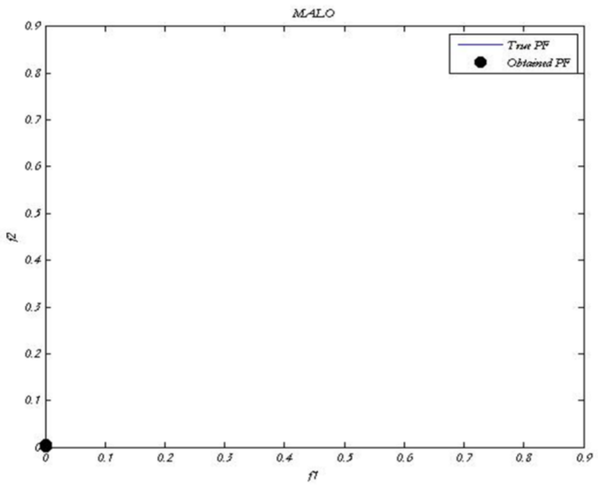

Figure 5: Fitness Response for 5000iterations

TABLE 6: OPTIMIZED DECISION VARIABLES (ODVS) AT 5000ITERATIONS

Boundary Variable	Opt. Value
kc1	0.0441
kc2	1.3598
kc3	0.0022
kd1	0.6316
kd2	1.4991
kd3	0.0020
kc	0.0385
kd	-0.5363

V. Discussion and Conclution

This research study has proposed an Updated Multi-Objective Ant-Lion Optimizer (UMO-ALO) for modeling of Open Circuit Voltage (OCV) state-of-charge (SOC) of Lithium-ion cells with cathode-anode composition (LiMnO2/Li4TiO). The proposed approach is based on the optimization of real time data obtained from laboratory-type battery cell charge/discharge cycle measurements while considering the First-Order Transient Response (FOTR) mode.

Basing on a dual objective of minimizing the battery cell SOC error difference for the simultaneous case of charge and discharge cycles, a model fit describing the SOC for the aforementioned cell composition was obtained after different UMO-ALO trial run simulation configurations.

Considering a default UMO-ALO trial run of 100iterations, a fitness response close to the zero-margin is clearly observable (see Figure 2 – Figure 4). Also, the estimated coefficients of the battery cell FOTR model parameters for this configuration are as shown in Table 5. Though, there are some variations in the result shown in Table 5, the fitness response is still adequate for any of the trial runs.

By increasing the trial run from default value to 5000iterations, a much closer fit to the zero-margin is obtainable. However, the error margins are still comparable to that of the default trial runs.

Thus, basing on the aforementioned results, and using very small training dataset, the UMO-ALO is recommended as an approximate model for the modeling OCV-SOC of Lithium-ion cells.

VI. Acknowldgement

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NOMENCLATURE

$cumsum$ - a cumulative sum function

n - maximum number of iterations of the ALO

t - iteration step

r - random function

a_i - a lower-bound of random walk in *i-th* ant variable

b_i - an upper-bound of random walk in *i-th* ant variable

l_i^t - minimum of *i-th* ant variable in *t-th* iteration

u_i^t - maximum of *i-th* ant variable in *t-th* iteration

I - decrement ratio

T - maximum number of iterations

w - exploitation (accuracy adjustment) factor

$Antlion_j^t$ - position of the chosen *j-th* ant-lion at *t-th* iteration

Ant_i^t - position of the captured *i-th* ant at *t-th* iteration

R_A^t - ant random walk selected by roulette wheel at *t-th* iteration

R_E^t - ant random walk around elite at *t-th* iteration

k_{c1} - Charging Coefficient of R0

k_{c2} - Charging Coefficient of R1

k_{c3} - Charging Coefficient of τ

k_{d1} - Discharging Coefficient of R0

k_{d2} - Discharging Coefficient of R1

k_{d3} - Discharging Coefficient of τ

k_c - Charging constant term

k_d - Discharging constant term