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Comparison of the performances of heuristic optimization algorithms PSO, ABC and GA for parameter estimation in the discharge processes of Li-NMC battery

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Abstract: The effects of the studies performed for the development of cells, which are the fundamental components of electrochemical battery units are felt in many different areas such as electric rail transportation systems, battery-based energy storage systems, battery units in electric vehicles, and energy storage units for individual use. For this goal, studies conducted by other searchers in the similar field have been investigated. In this paper, optimization techniques are used to guess the model parameters with major righteousness using the electrical equivalent circuit model of the battery. The discharge processes of the 18650 cylindrical type 2000 mAh Li-NCM battery cell with 1 A pulsed constant current at 25 ºC have been investigated. The real parameter values obtained have been transferred to the electrical equivalent circuit model. The open circuit voltage is determined as a functional term depending on the state of current supply level by using the curve fitting method in the Matlab. Studies have been carried out on particle swarm optimization algorithm, artificial bee colony algorithm, and genetic algorithm to estimate the battery output terminal voltage by using the open circuit voltage. Comparisons have been made and differences have been analyzed between the technics by using different statistical methods of true error values, the correct prediction ability, and response speed. As a result, the optimization method that makes the most accurate estimation has been determined.

***Keywords**:* *ABC, GA, Li-ion battery, Parameter estimation, PSO*

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1. INTRODUCTION

In order to ensure reliable, stable, and efficient energy flow in battery-based energy storage units, which are frequently encountered in daily life, charge/discharge processes should be monitored and functional optimization studies used in these processes should be identified. It is noteworthy to use a appropriate battery model to select the preferred algorithm parameters in optimization processes with acceptable accuracy. Although the price of lithium-ion (Li-Ion) battery cells is predicted to decrease by about 60% in the near future [1], it is obvious that the use of an accurate battery model and appropriate optimization algorithms will provide additional benefits. Model-based control and prediction algorithms provide better utilization of cell performance, safety, and longevity by protecting against the root causes of battery cell deterioration [2].

The correct selection of the model and optimization way enables more certain conclusions to be obtained in simulation studies that can be adapted to practical studies. Another issue affecting the correct parameter estimation is the charge/discharge profile [3]. There are many charging and discharging methods used in current studies. Charge/discharge types have advantages/disadvantages relative to each other, depending on where they are used. When the case studies in the literature on detailing the preferred discharge topologies in the study are examined [4,5], it is seen that the pulsed constant current (PCC) is suitable for the study. The frequent use of constant current (CC) in industrial applications and the updating of the parameters at each pulse of the pulsed current (PC) have been effective in the use of PCC in paper [6]. Open circuit voltage (V_{oc}) and state of charge (SoC) can be included in significant parameters in PCC discharge processes [7]. V_{oc} is a critical variable in determining the characteristics of the battery cell and the electrode in the cell structure. The V_{oc} curve, which varies depending on the SoC in the study, plays a significant role in knowing the electrode properties of the battery cell with the help of the rest period after the kinetic processes [8].

Table 1. Studies on PSO, GA, and ABC optimization methods used for parameter estimations of batteries in the last 10 years

Used Method	Paper Year	Researcher(s)	Battery Model	Chemical Structure	Used Parameter	Estimated Parameter
PSO	2012	Hu etc. [9]	Thevenin EECM.	Li-NMC, Li-$FePO_4$	*SoC, T*	V_{oc}
	2016	Mesbani etc. [10]	Thevenin EECM.	Li-NMC	*SoC*	V_{oc}, R_Ω
	2018	Kai etc. [11]	Thevenin EECM.	Li-Ion	*SoC*	V_{oc}
	2020	Li etc. [12]	Thevenin EECM.	Li-Ion	*SoC*	V_{oc}
GA	2016	Sangwan etc. [13]	Developed Thevenin EECM.	Li-Ion	*T, I, SoC*	V_{oc}
	2017	Chen etc. [14]	Thevenin EECM.	Li-NMC	*SoC*	V_{oc}, V_T
	2018	Brondani etc. [15]	Shepherd Model.	Li-Po	I, V_{oc}, T	η, N_c
	2020	Carmona etc. [16]	Developed Thevenin EECM.	Li-CO	*SoC*	V_{oc}, R_Ω
ABC	2015	Patil etc. [17]	Support Vector Machine Classification Model and Regression Model.	Li-Ion	N_c	C_{cap}
	2019	Wang etc. [18]	Support Vector Regression.	Li-Ion	N_c	C_{cap}
	2021	Zhang etc. [19]	Single Linear Model, Machine Learning Model.	Li-Ion	C_{cap}	N_c
	2022	Yan etc. [20]	Empirical Model, Exponential Model.	Li-Ion	N_c	C_{cap}
PSO, GA, ABC	2022	Çarkıt and Alçı [This Study]	Thevenin EECM.	Li-NMC	*SoC*	V_T

In studies conducted by different researchers in previous years, it is potential to encounter studies based on parameter estimation of Li-Ion batteries. Among these studies, parameter estimation applications of batteries are made by using various algorithms and optimization methods. Some of the studies conducted in the literature regarding the techniques used in the paper are shown in Table 1 in a classified way. As seen in the table, while parameters such as SoC, terminal voltage (V_T), temperature (T), internal resistance (R_Ω), charge/discharge efficiency (η), current (I), number of cycles (N_c), and current capacity (C_{cap}) are predicted in some studies, they are taken into account as a factor affecting the estimation in other studies. In addition, there are limited number of estimation processes made with artificial bee colony (ABC) in the literature. In studies involving such new generation algorithms, methods with artificial technologies are preferred as battery model.

In this study, which is different from its counterparts in the literature, the V_T value of the battery cell is tried to be estimated accurately by using ABC algorithm, which is a current optimization method, genetic algorithm (GA), which is one of the traditional methods, and particle swarm optimization (PSO), that is a fundamental method. In addition, the application of ABC to the electrical equivalent circuit model (EECM) in the study increases the number of resources by contributing to the literature for battery parameter estimation. V_{oc} and V_T are defined as a functional expression linked to the SoC within the study. By using optimization methods, it is investigated which algorithm exhibits more successful results in V_T estimation. In the literature, different methods are used to compare multiple optimization methods with each other, as listed below [21-27]:

- *Absolute error (AE),*
- *Mean absolute error (MAE),*
- *Mean squared error (MSE),*
- *Least square of errors (LSE),*
- *The sum of LSE or mean LSE (SLSE or MLSE),*
- *Root mean squared error (RMSE),*
- *Mean percentage error (MPE),*
- *Mean absolute percentage error (MAPE),*
- *Coefficient of determination (R^2),*
- *Standard deviation,*
- *The best value,*
- *The worst value…etc.*

Inspired by the methods used in different studies in the field of battery technologies LSE, maximum LSE, mean LSE, MAPE, MAE, and RMSE of AE values are taken into account for comparing the techniques in this paper with each other. In addition, the response times are included in the comparison to obtain information about the speed of the optimization methods. As the objective function of the optimization methods, it is desired that the errors between the actual data and the predicted results are minimal by following the LSE, maximum LSE, mean LSE, MAPE, MAE, and RMSE of the algorithmic prediction data.

The sections of this study are organized as follows: In Section 2, information is given about the EECMs of Li-Ion batteries, which are among today's technological studies. How to calculate the parameters of the model and the points to be considered in the calculation are mentioned. In Section 3, detailed information about the optimization methods used in parameter estimation is given. The experimental discharge result obtained from the database for the Li-NMC battery cell and the outputs of the optimization methods are compared in Section 4. In Section 5, which constitutes the conclusion of the study, inferences are made by interpreting the maximum values of the squares of errors (SE), the mean values of squares of errors (MSE), and the response rates of the estimation methods.

2. CREATING THE BATTERY MODEL AND DETERMINING THE PARAMETERS

For the selection of the circuit model aimed to be used in optimization-based parameter estimation and computer-based simulation application, Thevenin EECM of the battery with one *R//C* block, which is illustrated in Fig. 1, has been preferred. In choosing this model, the experience of the authors' previous study is used [28, 29]. This model provides the following outputs and parameters for Li-NMC battery units:

- *R_Ω change and voltage decrease across the ohmic resistor,*
- *Long/short term transient behavior caused by polarization effect,*
- *SoC effect that changes according to discharge current and discharge time,*

- *The efficacy of enhancement N_c on the discharge state,*
- *Charge/discharge transfer polarization effect.*

The EEC model being given in Fig. 1 shows V_{oc} as the internal voltage source. The voltage drop due to the R_Ω of the battery cell is considered as the loss that turns into heat, which is called the copper loss [30]. In the recovery operation later the discharge is ended, the polarization capacity C_p, which is accepted as the transient capacity, and the transient resistance R_p are effective in determining the short and long term transient behavior of the battery. The voltage drop on the $R_p//C_p$ arm of the circuit model is due to the polarization effect and is represented by V_p.

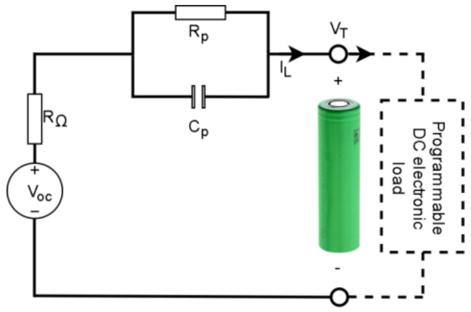


Figure 1. Electrical equivalent circuit model of the battery

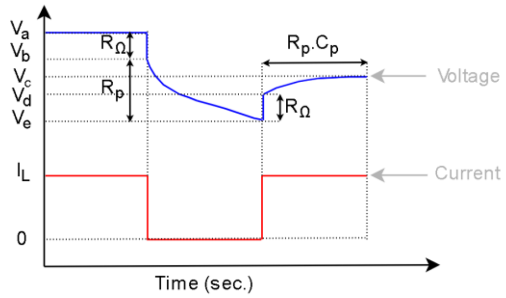


Figure 2. An example discharge step and model parameters

$$R_\Omega = \frac{V_a - V_b}{I_L} \tag{1}$$

$$R_p = \frac{| V_e - V_c |}{I_L} \tag{2}$$

$$V_p = I_L \, R_p \, e^{\frac{-t}{\mathcal{T}}} \tag{3}$$

$$V_T = V_{oc} - I_L \, R_\Omega - I_L \, R_p \, e^{(\frac{-t}{\mathcal{T}})} \tag{4}$$

The instantaneous voltage drop in Fig. 2 is used to calculate the R_Ω on the model of the Li-NMC battery cell given in Fig. 1. The expression in Eq. (1) is used to calculate R_Ω. In this expression, the cell voltage before the discharge process starts is V_a, cell voltage at the moment when the load is activated and the discharge process starts is V_b [31]. Similar to R_Ω, Eq. (2) is used to calculate R_p [32]. In this equation, V_e is the cell voltage after discharge process. In the equation, V_c defines the cell voltage that reaches equilibrium after the rescue effect. The V_p used in the determination of the polarization losses in the model is obtained by using Eq. (3). In this equation, t defines the discharge step time and is accepted as 1 second. Eq. (4) is used to calculate V_{oc} with model-dependent arithmetic methods. In the equation, the output terminal voltage of the battery cell is V_T, the time constant $\mathcal{T}$, which is equal to the multiplication of the polarization resistance and the capacitance.

3. OPTIMIZATION METHODS USED IN PARAMETER ESTIMATION

Optimization methods, which are defined as finding the best, are generally examined under two main headings: Classical methods and heuristic methods. Classical optimization methods reveal some inadequacies on the subject discussed in this study owing to their properties like as:

- *The existence of uncertainties in various algorithms,*
- *The program may terminate at unwanted times due to limited memory size,*
- *Not having the flexibility to respond quickly to changes [33].*

Another method in the optimization topology is heuristic optimization methods. Heuristic methods are frequently preferred in studies due to their features such as;

- *Ability to instantly adapt to changes in algorithms and formulas in flowcharts,*
- *Be able to read a widespread space of solutions quickly,*
- *Approach to the most appropriate solution.*

ABC and PSO algorithms based on swarm intelligence are preferred because of their advantages on "accurate estimation of battery parameters", which is the focus of this study. In addition, it is aimed to compare the performance outputs of the optimization methods as a result of using GA among the heuristic methods based on development. The fact that ABC is a current and widely used algorithm, PSO is a swarm-based fundamental algorithm, and GA is frequently preferred in dissimilar works in the literature have been effective in the selection of these techniques.

3.1. Artificial Bee Colony Optimization Algorithm

ABC, one of the most recent heuristic optimization methods, has been developed by Karaboga in 2004 to solve numerical problems [34]. Inspired by the movement and type of communication of bee groups in habitat, ABC is a optimization procedure based on the segmentation of labor that bees do by instinctively classifying them as employees, discoverers and observers for providing nutrition [35]. As in swarm intelligence-based methods, ABC also has the opportunity to self-organize and share work without a command from the command center. In the ABC, that is a assembling of global and local search methods, each iteration consists of three main stages with bee class names and functions: employed bee stage, onlooker bee stage, and scout bee stage [36]. In the decision-making process in ABC, there are traces of the collective decision-making approach used by the bees in the natural life in their daily processes [26].

Solutions presented for the issue in ABC show the position of nutrient resources. The quantity of nourishment in nutrient centers matches to the suitability of the answers presented to the problem. In other words, it corresponds to the qualification of the resolutions. The number of foods in the springs interrelates with the qualification of the results [37]. For obtaining the best consequence in algorithm, firstly Eq. (5) is used to generate the nutrition source regions symbolized by X_{ij}. The suitability rate is computed as in Eq. (6) with respect to the case of aim function. The aliment source is chosen using Eq. (7) and then the employed bees are organized for directing through the goal. The fitness value in Eq. (8) is regarded for seeing selection status of the food sources by the relevant bees. In Eq. (8), the food source variable rank is i, dimension rank is j, fitness function is f_{it}, objective function is f, the probability of choosing the source is p_i, the total number of worker bees is represented by TB. λ defines a haphazard numeral between 0 and 1. The φ, which provides the displacement operation, represents the random count between -1 and 1. X^{max} and X^{min} define the lower and upper bound limits of the relevant variable. The number k represents a random value chosen from the numbers starting from 1 to the number of food. Some of the reasons why ABC is preferred in studies are listed below:

- *Based on herd intelligence,*
- *Having flexible behavior,*
- *Easy to adapt,*
- *Uses few control parameters*
- *Simultaneous execution of the search for local and global optimum within the algorithm [38],*
- *Does not need mutation and crossover rates that determine priority,*
- *It has a balanced use and exploration ability [39].*

$$X_{ij} = X_j^{min} + \lambda\,(X_j^{max} - X_j^{min}) \tag{5}$$

$$f_{it} = \begin{Bmatrix} 1/(1+f & f \geq 0 \\ 1+|f| & f < 0 \end{Bmatrix} \tag{6}$$

$$X_{new} = X_{ij} + \varphi\,(X_{ij} - X_{kj}) \tag{7}$$

$$p_i = \frac{f_{it_j}}{\sum_{j=1}^{TB} f_{it_j}} \tag{8}$$

3.2. Particle Swarm Optimization Algorithm

This algorithm has been gived form by Kennedy & Eberhart in 1995. Like many optimization techniques, PSO is inspired by the life cycle in nature and the behavior in this cycle. During the creation of the PSO, the behavior of fish, insect and bird herds (population) has been observed and transferred to the algorithm [40]. This method that is proposed for the remedy of nonlinear issues is used for the solution of multivariate and multi-parameter problems. Some causes why PSO is given priority in scientific studies in many varied fields are listed below:

- *Ability to offer high quality solutions within short calculations,*
- *Ability to provide acceptable solutions to single-purpose or multi-purpose target functions [41],*
- *The low number of parameters to be adjusted [42],*
- *Does not need derivative information,*
- *It is not complicated to set up in a computer [43],*
- *It can give fast and effective results [44],*
- *It can exhibit a stable convergence property [45].*

$$v_{nm+1} = w\, v_{nm} + c_1\, \lambda_1\, (p_{nm}^{best} - x_{nm}) + c_2\, \lambda_2\, (s_{nm}^{best} - x_{nm}) \quad (9)$$

$$x_{nm+1} = x_{nm} + v_{nm+1} \quad (10)$$

In the operation of PSO, natural particles in the herd act casually for arrive the aim. All individual strives to make its present situation similar to the situation of the best particle in the swarm. By adopting the principle of continuous improvement, the particles aim to become better than their former location in each reiteration. To achieve this goal, each individual uses the direction-related speed vector in Eq. (9) and location-related position vector in Eq. (10). In the equations, w is inertia coefficient, c_1 and c_2 are scaling factors, λ_1 and λ_2 are step sizes which are included in the equations as random numbers chosen between 0 and 1. According to the coefficients c_1, c_2, λ_1 and λ_2, the PSO algorithm searches for both local and global solutions [46]. Due to the possibility that local solutions are global solutions, λ_1 and λ_2 take random values in the specified range. m is the number of iterations, v_{nm} is the velocity of the n^{th} particle at the m^{th} iteration, $m+1$ is the following repeat value, p^{best} and s^{best} are accepted as the best of the particle and the swarm respectively. When the velocity equation is divided into three different parts and the expressions are followed, the mathematical term in the introduction indicates the claim of each particle in the swarm to sustain its previous position. This condition can be related to the inertia weight, which is an important optimization parameter interest to the past acceleration. These parameters are an important factor to facilitate reaching the local optimum and the global optimum [47]. In the second part of the Eq. (9), the particle remembers its best position and wants to update its position accordingly. In the last part of the equation; the particle remembers the position of the best of the swarm and wants to update itself accordingly.

3.3. Genetic Algorithm

Among the heuristic methods, the GA process, which is one of the versions of evolutionary algorithms (EA) based on probability-based development, is frequently encountered in the literature. Based on the principle of natural selectivity and evolution, GA has been studied on binary codes by Holland and researches in the 1970s. When GA is coded appropriately, it can offer acceptable solutions to real-life problems. GA, that is an adaptable optimization procedure, is based on the way of using the most skilled solutions by looking for convenient individuals in the prior generations to achieve the following generations. This scanning, which is included in evolutionary algorithms, can be included in meta-heuristic techniques in some scientific researches. GA is frequently used to create convenient resolutions to optimization topics that are in engineering [48].

Searching for a global solution rather than a local one, GA uses codes instead of actual parameter values when searching for the solution. GA is based on the survival of individuals who adapt to the living conditions of the environment and the disappearance of those who cannot adapt. Since the genes of an individual are subject to mutation or crossover processes for different reasons, new generations are derived due to such changes in the genes. It is aimed to get the best consequence from the solution space, which includes existing genes and genes resulting from changes. Some of the reasons why GA is preferred in studies are listed below:

- *Based upon the principle of natural selectivity, adaptation and evolution,*
- *Does not need estimation about the solution region,*
- *Does not need derivative information,*
- *Being resistant to irregular problem formulations [49],*
- *Being resistant to equational constraints,*
- *Using encodings instead of actual parameter values.*

$$p_i = \frac{f}{\sum f} \tag{11}$$

$$c_i = c_{i-1} + p_i \tag{12}$$

$$tp_{ij} = tp_{ij} + \alpha \Delta \, (ub_j - lb_j) \tag{13}$$

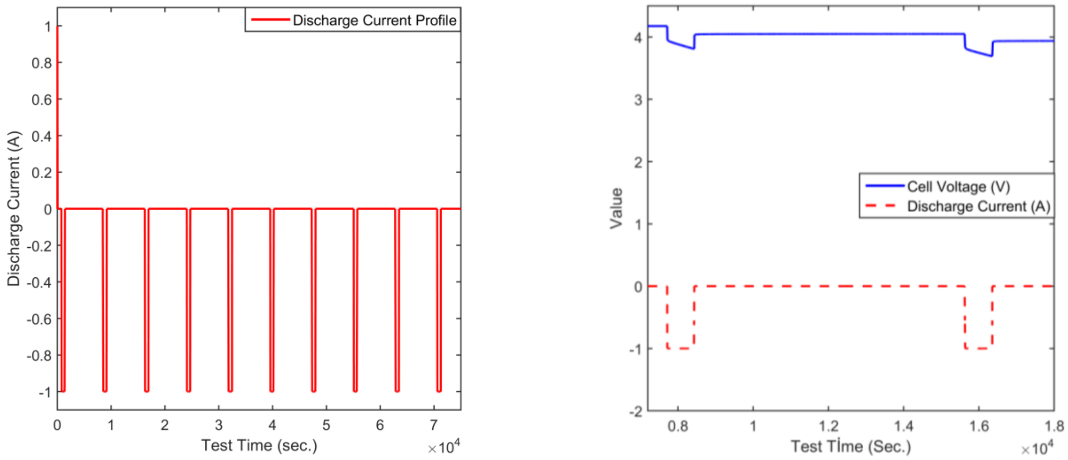
It is known that three basic functions occur for GA as selection, crossover and mutation. In Eq. (11), p_i is the probability of survival and f is the objective function. Eq. (12) is used to calculate the cumulative probability "c_i" required for selection. Eq. (13) is used to obtain the intermediate population resulting from the operators. In the equation, α represents the randomly selected number, tp is the intermediate population, Δ defines the neighborhood ratio, ub represents the upper limit, and lb is the lower limit. The parameters of the optimization ways used in the paper are presented in Table 2. Forecasting simulation studies have been carried out according to these parameters.

Table 2. Parameters of optimization algorithm

Algorithm	Initial Optimization Parameters
ABC	Dimension = 8 Colony Size = 64 Repetition = 100 Food Source = 128 Limit = 256 Selection Type = Greedy Selection
GA	Dimension = 8 Population Size = 64 Repetition = 100 Crossover Ratio = 0.9 Mutation Rate = 0.005 Neighborhood Ratio = 0.05 Selection Type = Roulette Wheel
PSO	Dimension = 8 Swarm Size = 64 Repetition = 100 Inertia Parameter = 0.8 Social Coefficient = 1 Cognitive Coefficient = 1

4. COMPARISON OF EXPERIMENTAL DATA WITH SIMULATION RESULTS

The preference of Li-NMC battery cells, especially in electric vehicles and individual user-sized energy storage systems, has been the motivation for this paper. The test data of the 18650 cylindrical type 2000 mAh Li-NCM electrochemical battery cell by the University of Maryland CALCE Battery Research Group have been examined [50]. Referring to Fig. 2 and Fig. 3, the sample PCC profile used in the experimental tests has a 7200 second rest and recovery time after a 720 seconds discharge process per pulse. During the discharge test performed with a 1 A PCC in accordance with the current profile at 25 ºC, the voltage of the battery cell changes as in Fig. 4. Although the data obtained at different temperatures can be analyzed, the effect of temperature on the parameters constitutes a different study subject. Therefore, 25 ºC, which is the optimum working environment and room temperature, has been preferred in the paper.



(a) *(b)*

Figure 3. Performed with pulsed constant current; a) PCC discharge profile, b) a sample discharge pulse current and voltage information

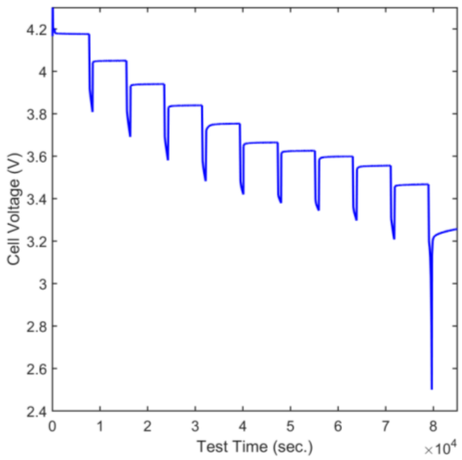


Figure 4. Variation of cell voltage depending on discharge profile.

Parameter calculations are made by adapting the obtained data to the battery model in Fig. 1. At this stage, the exponential function in Eq. (14) and Eq. (15) is used. In the equation, "$y_{1...5}$" values represent dynamic coefficients that can take different values according to changing environmental conditions. In the expression in Eq. (15), which allows dynamically changes in the coefficients, the coefficients of "$y_{1...5}$" are updated by the algorithm at the SoC level where each data is taken. Although this situation increases the complexity of the process, it provides the opportunity to achieve more successful results that can be adapted to practical studies, have high adaptability. Limit values of these coefficients are given in Table 3. While defining V_{oc}, SoC is taken into account as the dependent state variable. On the other hand, since the temperature is taken as 25 ºC, the effect of temperature on the parameters is neglected. In the literature, at the stage of defining the parameters depending on the variables, the regression coefficient is required to be greater than 95% [51, 52].

In this study, it is desired that the regression coefficient is especially greater than 99%. In addition, when using the parameters obtained as a result of the experimental results and the estimation process, it is desired that the absolute error and the squares of the errors should be as close to 0 as possible. In accordance with these conditions, the V_T equation created with the help of curve fitting method (CF) according to the SoC change and planned to be used in optimization processes is expressed as in Eq. (16). The circuit model in Fig. 1 and the mathematical definitions in Eq. (4) and Eq. (15) are used to create the equation. Although R_Ω, R_p parameters depend on SoC, they are selected by the algorithm according to the lower limit (*lb*) and upper limit (*ub*) values in Table 3 in accordance with the optimization problem. The advantage of this selection is that the R_{Ω} and R_p values are also optimized within themselves. The *lb* and *ub* values have been chosen according to the internal resistance and polarization resistance variation in Fig. 5 obtained by reading the experimental data and discharge graph. The limits of $y_{1...5}$ parameters are formed by expanding the coefficient ranges obtained by the CF method.

$$V_{oc} = f^{3}_{(SoC)} \tag{14}$$

$$V_{oc(SoC)} = y_1\, e^{(-35\, SoC)} + y_2\, (SoC)^3 + y_3\, (SoC)^2 + y_4\, (SoC) + y_5 \tag{15}$$

$$V_T = V_{oc(SoC)} - I_L\, R_{\Omega} - I_L\, R_p\, e^{\frac{-t}{T}} \tag{16}$$

$$SoC_{t+1} = SoC_t + \frac{\int_t^{t+1} I_L\, dt}{3600\, C_{ref}} \tag{17}$$

$$\left\{ \begin{array}{c} e = |V_{real} - V_{est}| \\ SE = e^2 \\ MSE = \frac{1}{n} \sum_{1}^{n} (e^2) \\ RMSE = \sqrt{\frac{\sum_1^n (e^2)}{n}} \\ MAE = \frac{\sum_1^n |e|}{n} \\ MAPE = 100. \frac{\sum_1^n \frac{|e|}{V_{real}}}{n} \\ R_{\Omega}^{max} > R_{\Omega} > R_{\Omega}^{min} \\ R_p^{max} > R_p > R_p^{min} \\ C_p^{max} > C_p > C_p^{min} \\ y^{max} > y > y^{min} \\ f = min(SE) \end{array} \right\} \tag{18}$$

Table 3. Limits of battery model parameters

Bound	R_{Ω}	R_p	$y_{1...5}$
lb	0.1079	0.0523	-100
ub	0.3170	0.8077	+100

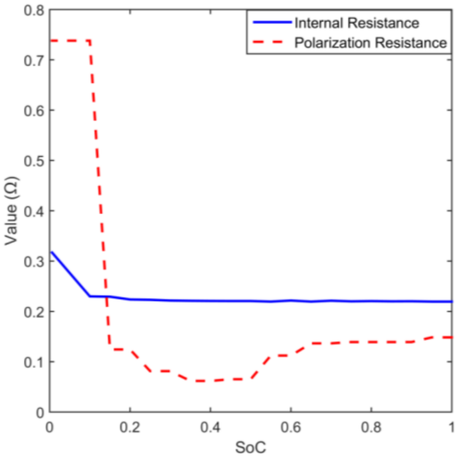
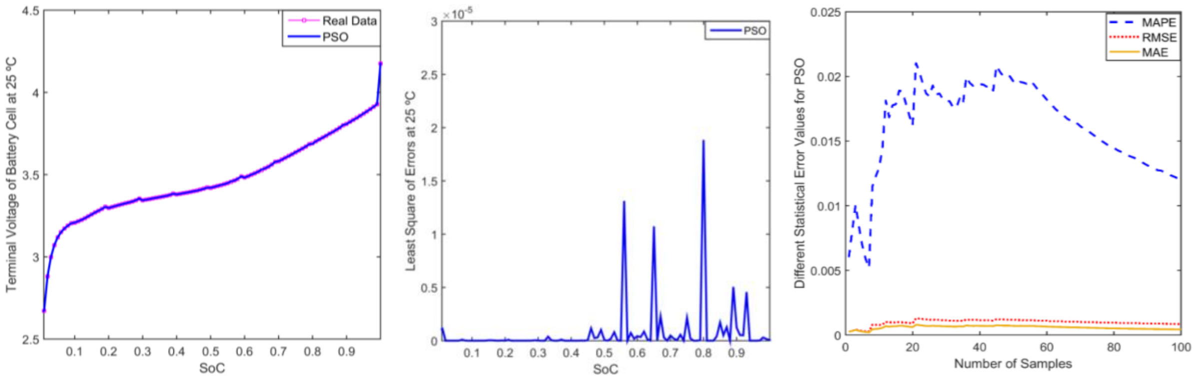


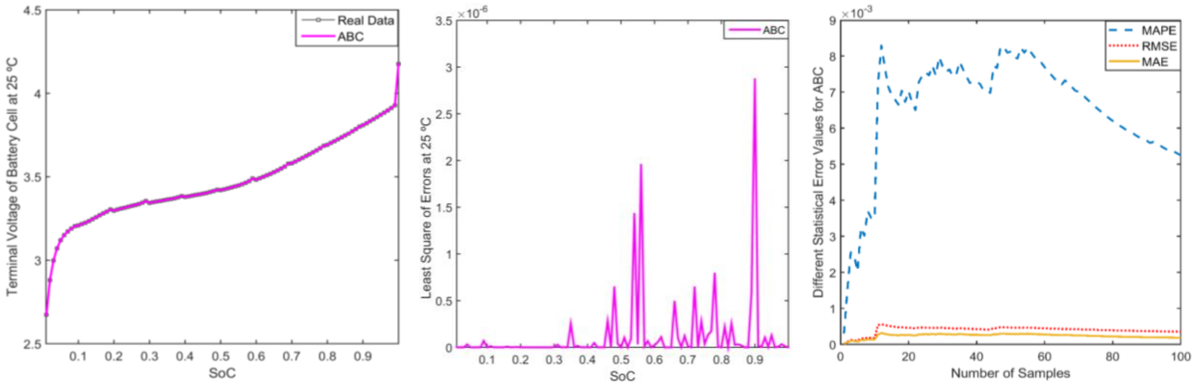
Figure 5. Change of actual values of R_{Ω} and R_p according to SoC in 20 sample points.



(a) (b) (c)

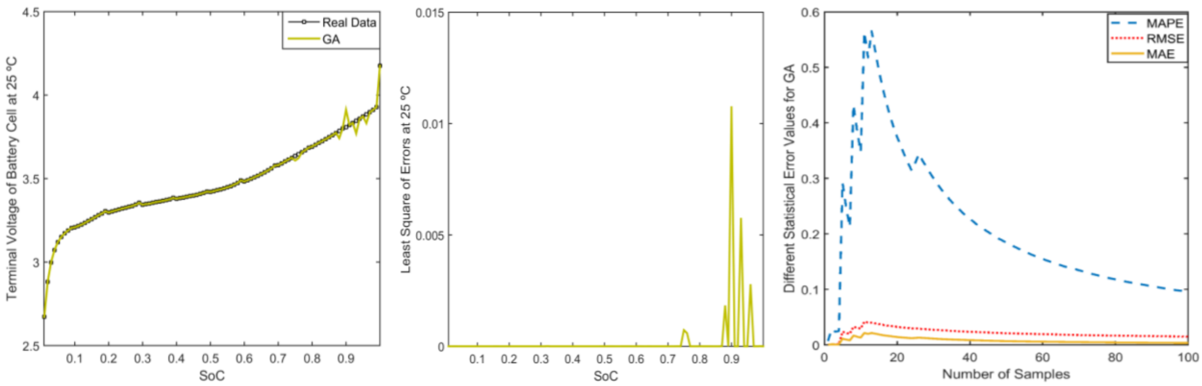
Figure 6. In the PSO algorithm; a) Actual data and optimization prediction values, b) LSE values between actual data and optimization data, c) Different Statistical Error Values for PSO

The variation of the SoC is obtained by using the "ampere hour" count in Eq. (17) depending on the time. In the equation, t represents the previous time and $t+1$ represents the next time. C_{ref} is the initial current holding capacity of the battery and is included in the calculation of the SoC. Limit and purpose information used in optimization studies made in line with the information given in Section 3 and Section 4 up to this point are given in Eq. (18). In the equation, the absolute error is expressed as e, the experimental test result of the terminal voltage is V_{real}, the estimated terminal voltage value is V_{est} that is as a result of the optimization, the squares of the errors are SE, the the mean value of the summation of the squares of the errors is MSE, the number of data is n, the objective function is f.



(a) (b) (c)

Figure 7. In ABC algorithm, a) actual data and optimization prediction values, b) LSE values between actual data and optimization data, c) different statistical error values for ABC.



(a) (b) (c)

Figure 8. In GA, a) actual data and optimization prediction values, b) LSE values between actual data and optimization data, c) different statistical error values for GA.

Table 4. Comparison of algorithmic simulation results for V_T.

Temperature (ºC)	Algorithm	Max. Time for Each Iteration	Mean Time for Each Iteration	Max. LSE	Mean LSE	MAPE	MAE	RMSE
25	ABC	2.1878	1.6798	$(2.8797).10^{6}$	$(1.2443).10^{7}$	0.0053	$(1.8718).10^{4}$	$(3.5275).10^{4}$
	PSO	10.989	10.035	$(1.8854).10^{5}$	$(7.3431).10^{7}$	0.0123	$(4.3857).10^{4}$	$(8.5692).10^{4}$
	GA	1.2864	0.9911	0.0108	$(2.2301).10^{4}$	0.0948	0.0036	0.0149

```
Describe input parameters
Defining objective function
Defining fitness value
Generate initial population randomly;
    for i = 1: Colony size
    for j = 1: Parameter size
    end
    end
Calculate objective function value
Calculate fitness value;
    for i = 1: Colony size
    for j = 1: Parameter size
    end
    end
ABC main loop start;
for iteration = 1: maximum iteration
Employed bee phase
        Generate new solution;
        Calculate objective function value
        Calculate fitness value
        Perform greedy selection
        for i = 1: Colony size
        for j = 1: Parameter size
Onlooker bee phase
        Calculation of probability fitness value;
        end
        end
        for i = 1: Colony size
            if (rand < p_i)
            Generate new solution
Scout bee phase
        H = find (trial > limit);
        if length (H) > 0
            Random population generation
            Calculate objective function value
            Calculate fitness value
        end
end iteration
            Calculate objective function value
            Calculate fitness value
            Perform greedy selection
            Memorize the best answer
        end
        end
```

Figure 9. Process steps for ABC algorithm.

Considering the experimental test results performed at 25 ºC, which is the optimum operating environment for battery systems, the V_T estimates of the PSO, ABC, GA methods and the error values of the estimations are given in Fig. 6, Fig. 7, and Fig. 8 respectively. Considering the V_T estimations, the error values of the estimations, and Table 4 the ABC algorithm presented the most successful result. Although PSO has the slowest response speed, it has performed well in second place. Though GA has the fastest response time, the performance quality in the simulation result is the lowest. Even though it is possible that to develop the efficiency of GA by adjusting the variables in the internal structure of the algorithm, GA is not considered suitable for the problem studied. The principal code flow chart of ABC, which offers the most successful results and has the potential to support practical studies, is given in Fig. 9 in line with the information in Section 3.1.

5. CONCLUSION

Since batteries exhibit non-linear behavior, it is important to perform parameter estimations with acceptable performance. High-accuracy predictive data gives more favorable results in computer-based studies that are planned to be transferred to applied studies. Working with the right parameters provides gains in terms of financial opportunities and time. In this direction, a study has been carried out on Li-NMC battery technologies, which are considered among the current technologies and are among the priority areas. By examining the sample discharge information taken from the database, the equations on how to calculate the parameters in accordance with the determined battery model have been obtained. Functional expressions have been defined using the Matlab program and the curve fitting method. Data obtained from ABC, PSO and GA optimization methods have been compared to estimate the terminal voltage. As a result of the comparisons, the artificial bee colony algorithm has revealed the most successful performance in the prediction processes for terminal voltage. After ABC, the PSO algorithm presented acceptable successful results. The GA which has the fastest response time, could not show the expected success. Eventually, it has been seen that the artificial bee colony algorithm is the most appropriate method in cases where both successful results and fast processing processes are desired.

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