Electromechanical Energy Conversion Systems (EECS),
Niroo Research Institute.
Vol. 1, Issue. 3 . Autumn 2019

ESTIMATION OF THE DYNAMIC PARAMETERS OF A BATTERY MODEL UNDER THE HYSTERESIS EFFECT EMPLOYING A HYBRID ALGORITHM OF PARTICLE SWARM OPTIMIZATION AND GREY WOLF OPTIMIZER

Hasan Mashayekh, Alireza Rezazadeh*

Faculty of Electrical and Computer Engineering, Shahid Beheshti University, Evin, Tehran, Iran

***Corresponding author,** *Email: a-rezazade@sbu.ac.ir*

Abstract

An accurate estimation of battery model parameters is essential for dynamic simulation of electric vehicles. Generally, parameterizing battery models are difficult and complex. Therefore it requires powerful estimation algorithms to overcome time-consuming and computational costs.

In this paper, the dynamic parameters of a battery model were estimated at 8 different temperatures and under the hysteresis effect. The estimation is based on a hybrid algorithm of particle swarm optimization and grey wolf optimizer. By this hybridization, the ability of exploitation in particle swarm optimization and the ability of exploration in grey wolf optimizer improved and both variants were empowered. The algorithm was implemented to estimate parameter values by minimizing the error between experimental data and the predicted results to find an optimal solution for an accurate model. Following a comparison with G.Plett's, the results indicated that the proposed algorithm can reach higher precision in the battery behavior because of the lower error possibility.

Keywords: Battery, parameter estimation, hysteresis

1. INTRODUCTION

Nowadays, electric vehicles are becoming more and more popular due to the rise in oil prices and the increase in greenhouse gas emissions [1]. One of the important parts of electric vehicles is batteries which store energy for their movement. There are different types of battery technology but lithium-ion batteries are the best technology for use in electric vehicles due to their high efficiency, high energy density, low self-discharge, high cycle life, and fast charging and discharging ability [2]. For knowing how Li-ion batteries perform in electric vehicles it is reasonable to use simulation methods instead of using real batteries for reducing costs and time during the design and development process [3]. It is important to model batteries' behavior and estimating the model's parameters accurately for simulating batteries' performance.

Generally, there are three different types of battery models as follows: (1) Electrochemical (2) Mathematical (3) Equivalent electrical circuit model [4][5]. Electrochemical models can predict all special behavior of a battery but they are computationally expensive and require extensive experimentation for estimating the parameters of the model [3][6]. The mathematical models use stochastic approaches or empirical equations to predict capacity, runtime, efficiency [7][8]. However, these models can't predict I-V characteristics of batteries therefore they are not suited for use in circuit simulation [9]. The equivalent circuit models are capable of predict I-V characteristics of batteries and suitable for dynamic electric vehicle simulations [10]. In these models, some resistors and capacitors represent battery electrochemical interaction [11].

There are various types of battery equivalent circuit models that some of them are presented in [12] such as combined model, simple model, zero hysteresis model, one-state hysteresis model, and enhanced self-correcting model (ESC). In [13] twelve equivalent circuit models were studied, and a multi-swarm particle swarm optimization algorithm used to estimate model parameters from experimental datasets which collected from two types of Li-ion battery. All these models were compared in terms of model

complexity, accuracy, and robustness. The authors in [14] estimated battery ECS model parameters at different temperatures with considering hysteresis. They used a lithium-polymer battery dataset and employed numerical optimization methods for estimation. As the same work, Plett in [15] used some different optimization methods to optimize and estimate battery dynamic parameters but he indicated that some of the battery parameters could be computed directly.
In this paper, a hybrid of particle swarm optimization and grey wolf optimizer (HPSPGWO) was employed for estimating ESC model dynamic parameters at 8 different temperatures under the hysteresis effect. The estimated parameter values compared with Plett's. The experimental data collected from a Li-ion battery and consists of some urban dynamometer drive schedule (UDDS) profiles as input current and some voltage profiles as output voltage. The rest of the paper as follows: Section 2 presents the ESC model. Section 3 presents the hysteresis effect. Section 4 the HPSOGWO algorithm is described. Section 5 presents the experimental data used for parameter estimation. Section 6 presents the estimation results and validation. Section 7 the conclusions are drawn.

2. ESC MODEL

This model includes a description of hysteresis, one or more parallel resistor-capacitor subcircuits for modeling the diffusion voltage, and one series resistance for modeling the ohmic voltage drop in a battery.
More number of parameters caused more complexity of the model. Equivalent circuit models with more than one RC subcircuit can represent a better behavior of battery dynamic performance and generate more accurate results. However, these models increase computational complexity and reduce numerical stability. The results of the paper [9] show that two parallel RC subcircuits can provide enough accurate results. But with one parallel RC subcircuit can make good enough results [17][18]. Thus we use one parallel RC subcircuit for our ESC model as Fig. 1 shows.

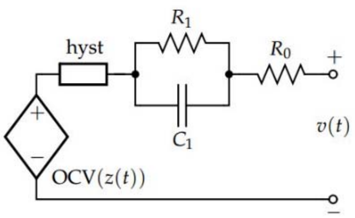

Fig. 1. ESC MODEL [15]

The model terminal voltage equation in discrete-time is:

$$V[k] = OCV(z[k], T[k]) + hyst\text{-}R_1 i_{R_1}[k]\text{-}R_0 i[k] \quad (1)$$

Where T[k] is the temperature, "hyst" term can described as next section and $i_{R_1}[k]$ also formulated as [14]:

$$i_{R_1}[k+1] = \exp\left(-\frac{\Delta t}{R_1 C_1}\right) i_{R_1}[k] + \left(1-\exp\left(-\frac{\Delta t}{R_1 C_1}\right)\right) i[k] \quad (2)$$

3. HYSTERESIS EFFECT

Experimental results show that if we discharge a battery to a specified state of charge (SOC) and allow the battery to rest, the equilibrium voltage is lower than the open-circuit voltage (OCV). If we charge a battery to that specified SOC as previous and allow the battery to rest, the equilibrium voltage is higher than OCV. This phenomenon indicates that there is hysteresis in the battery terminal voltage.

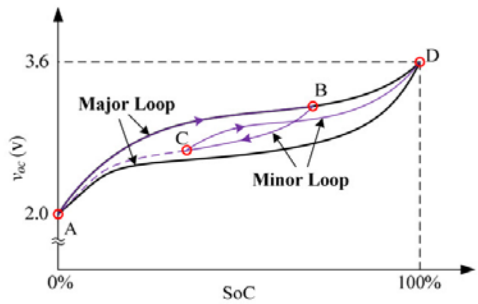

Fig. 2. HYSTERESIS MAJOR AND MINOR LOOP OVER CHARGING AND DISCHARGING CYCLES[19]

As Fig. 2 shows, there is a major loop of hysteresis effect that can be obtained by charging a battery with a very slowly charging current rate from point A (minimum voltage) to point D (maximum voltage) to a complete charging cycle and discharging it with a very slowly discharging current rate from point D (maximum voltage) to point A (minimum voltage) to a complete discharging cycle. Any partial charging/discharging cycle curve that would be located inside the major loop, is called hysteresis minor loop. For example, discharging a battery from point B to point C and then charging it from point C to point D will make a hysteresis minor loop[19].
The hysteresis model we use in this paper was reported by Plett in [15]. Plett divided hysteresis voltage into two separate parts and he unlinks it from OCV and other terms of battery to battery terminal voltage. One

part of hysteresis voltage is the hysteresis that changes as SOC changes and another part is the instantaneous hysteresis that changes as the sign of current changes.

3.1 SOC-varying hysteresis

This part of the hysteresis phenomenon depends on SOC. It can be expressed in the discrete-time as

$$H_1 = Mh[k] \tag{3}$$

Where M in volts is the maximum polarization due to hysteresis, k is the discrete-time index and h[k] is the unitless hysteresis function and can be written as

$$h[k+1] = \exp\left(-\left|\frac{\eta i[k]\gamma\Delta t}{Q}\right|\right)h[k] + \left(\exp\left(-\left|\frac{\eta i[k]\gamma\Delta t}{Q}\right|\right)-1\right)\operatorname{sgn}(i[k]) \tag{4}$$

Where unitless η is the coulombic efficiency, i[k] is applied battery current in amperes, positive constant γ is the rate of decay of hysteresis, Δt is the sample period, Q is battery capacity in coulombs and $\operatorname{sgn}(.)$ is the sign of its argument.

3.2 Instantaneous hysteresis

This part of the hysteresis depends on the input-current sign. The memory of the input-current sign is stored as

$$s[k] = \begin{cases} \operatorname{sgn}(i[k]) & |i[k]| > 0 \\ s[k-1] & \text{otherwise} \end{cases} \tag{5}$$

Then instantaneous hysteresis is modeled as

$$H_2 = M_0 s[k] \tag{6}$$

4. HPSOGWO ALGORITHM

This algorithm presented in [20], use a hybrid technique to give strength to particle swarm optimization (PSO) and grey wolf optimizer (GWO) and improve the exploration ability in PSO and exploration ability in GWO. This technique gives high quality and stability to the solutions and increases the speed of the algorithm to find the best solutions.

In this algorithm first, alpha, beta, and delta have to be specified as GWO. Then by multiplying an inertia constant (ω) to all wolf position, the exploration and exploitation of GWO could be controllable. Therefore GWO hunting process will encounter with a modification like :

$$\begin{aligned}
\vec{d}_\alpha &= |\vec{c}_1.\vec{x}_\alpha\text{-}\omega^*\vec{x}| \\
\vec{d}_\beta &= |\vec{c}_2.\vec{x}_\beta\text{-}\omega^*\vec{x}| \\
\vec{d}_\delta &= |\vec{c}_3.\vec{x}_\delta\text{-}\omega^*\vec{x}| \\
\vec{x}_1 &= \vec{x}_\alpha\text{-}\vec{a}_1.(\vec{d}_\alpha) \\
\vec{x}_2 &= \vec{x}_\beta\text{-}\vec{a}_2.(\vec{d}_\beta) \\
\vec{x}_3 &= \vec{x}_\delta\text{-}\vec{a}_3.(\vec{d}_\delta) \\
\vec{a}_{(.)} &= 2\vec{l}.\vec{r}_1\text{-}\vec{l} \\
\vec{c}_{(.)} &= 2.\vec{r}_2
\end{aligned} \tag{7}$$

Where $\vec{d}_\alpha$, $\vec{d}_\beta$, and $\vec{d}_\delta$ which are modified are distances between hunter and alpha, beta, and delta respectively, $\vec{x}$ is the vector of wolf position, $l \in [0,2]$.

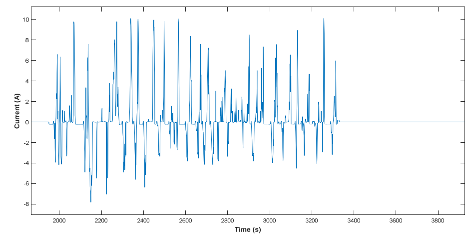

Fig. 3. UDDS PROFILE

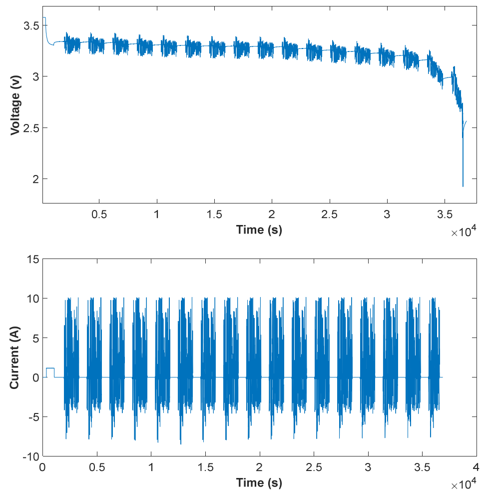

Fig. 4. BATTERY TERMINAL VOLTAGE AND CURRENT AT 25℃

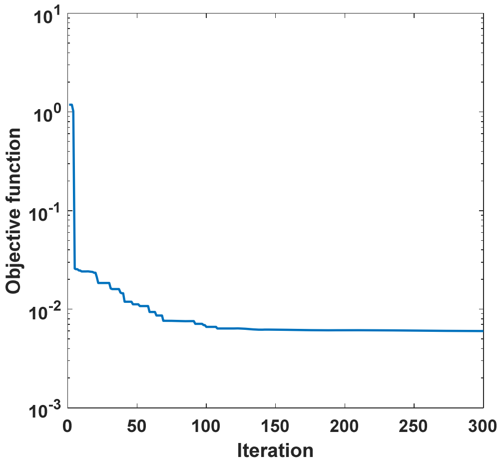

Fig. 5. CONVERGENCE PROCESS OF HPSOGWO AT 25℃

To mix PSO and GWO variants, the velocity and updated position are defined as

$$v_i^{k+1} = \omega^*(v_i^k + c_1 r_1(x_1\text{-}x_i^k) + c_2 r_2(x_2\text{-}x_i^k) + c_3 r_3(x_3\text{-}x_i^k))$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{8}$$

Where c_1, c_2 and c_3 are positive constant and r_1, r_2 and r_3 are random vector in [0,1].

TABLE. 1. ANR26650M1-B CELL SPECIFICATIONS

Dimensions	**∅ 26 × 65 mm**
Mass	76 g
Capacity	2.5 Ah
Nominal voltage	3.3 V
Internal impedance	6 mΩ
Operating temperature	-30℃ to 55℃
Discharge power	200 W

5. EXPERIMENTAL DATA

Data that we use here is obtained from [16]. It consists of 17 cycles of UDDS profile with a resting time between each cycle at 8 different temperatures. Fig. 3 shows a cycle of UDDS profile. The specification of the battery that undergoes this current profiles is summarized in TABLE. 1. It is a cylindrical and high power Li-ion battery used in transportation, commercial and, electric grid applications. The current and terminal voltage of this battery at 25°C is displayed in Fig. 4.

6. RESULTS AND VALIDATION

We run HPSOGWO with 300 iterations and 30 number of population for each temperature. All estimated parameters are compared with Plett's. Q, η which is calculated directly, and SOC-OCV relationship obtained from [16]. Therefore we have six unknown parameters. The unknown parameters' vector is $[R_0\ R\ C\ \gamma\ M\ M_0]$ that we try to estimate it. We expect as temperature increases, battery resistance decreases, and battery behavior speeds up. Thus we impose these behaviors as constraints to our algorithm.

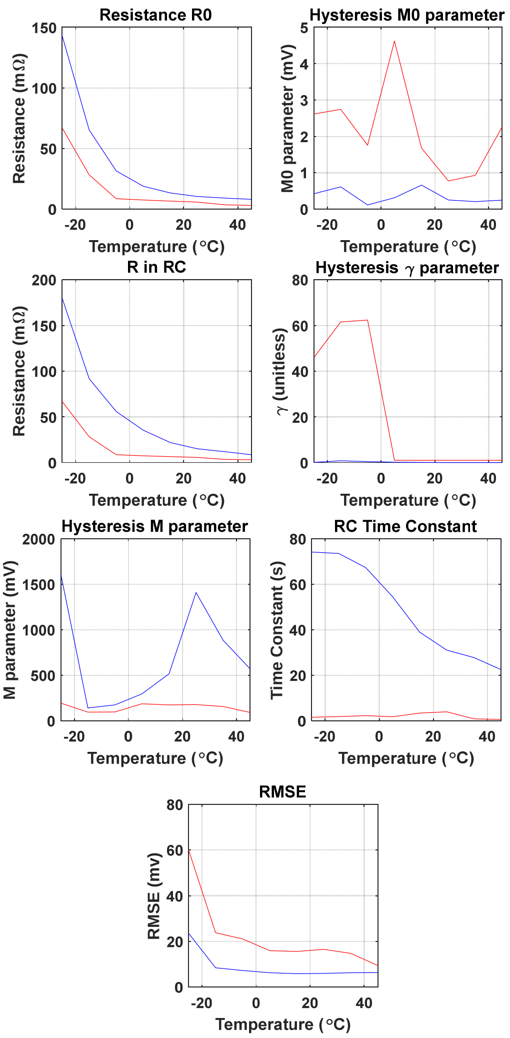

Fig. 6. ESTIMATION RESULTS. RED DIAGRAMS ARE RELATED TO PLETT'S MODEL PARAMETERS AND

BLUE ONES ARE RELATED TO THE PROPOSED MODEL

The algorithm tries to minimize the objective function or error between the experimental data and our model results. The root-mean-square error (RMSE) used as an objective function and is calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(V_{predicted}\text{-}V_{measured})^2} \tag{9}$$

Where n is the experimental data points. The convergence process of the algorithm at 25°C is illustrated in Fig. 5, indicating the best value of the objective function during the iterations.

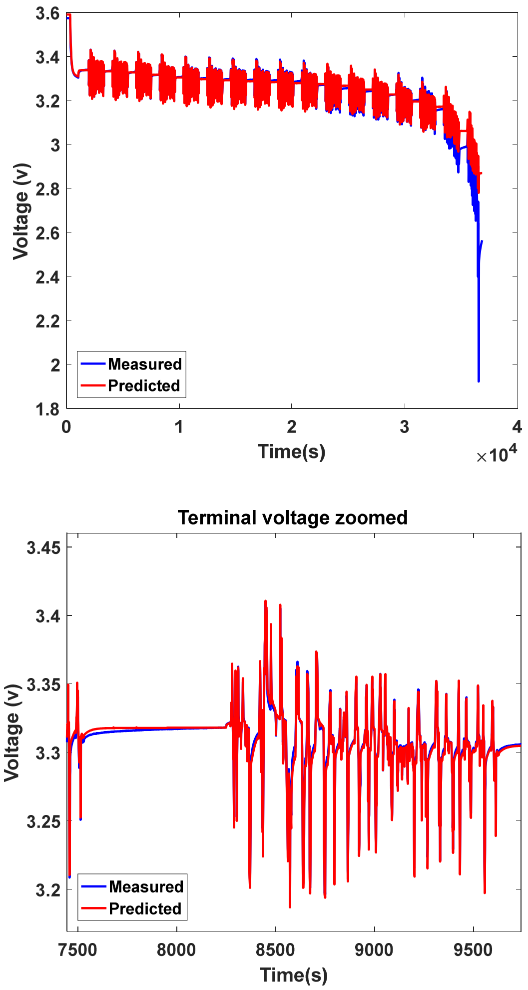

Fig. 7. PREDICTED TERMINAL VOLTAGE AND MEASURED TERMINAL VOLTAGE

Battery management systems (BMS) do not allow the battery to operate in out of range of SOC between 0.15 and 0.95 because of reliability and safety [21][22].

Fig. 6 shows the results of estimating battery dynamic parameters at 8 different temperatures. We can see from the RMSE diagram that our algorithm has a higher performance than Plett's estimation method at all temperatures because of the lower RMSE. The series resistance R_0 diagram and R diagram in RC exponentially decrease as temperature increases although we considered this reduction as constraints, this behavior is near-universal result.

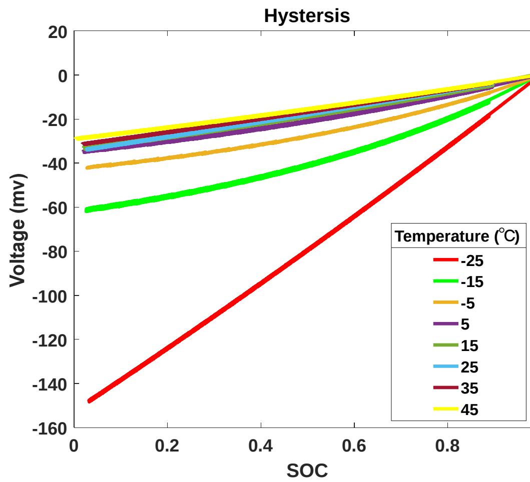

Fig. 8. HYSTERESIS VOLTAGE AT 8 DIFFERENT TEMPERATURES

Fig. 7 shows the results of the predicted terminal voltage in comparison with experimental data at 25°C. As we know when the battery is in the resting situation the voltage drop and battery transient behavior represent the ohmic resistance and RC time constant respectively. As Fig. 7 indicated the estimated terminal voltage is very close to the measured terminal voltage because of accurate estimation although we have lagged at the end of the discharge (low SOC), BMS do not let batteries operate in such low SOC range as mentioned.

According to Fig. 8 and RMSE diagram in Fig. 6 at the lower temperature battery has more nonlinear behavior due to the high influence of hysteresis at battery terminal voltage but as temperature increases, this effect strongly decreases.

7. CONCLUSION

this paper describes the development of a battery model, along with a prosses to estimate the model parameters from experimental data. The parametrization procedure is based on a hybrid algorithm of particle swarm and grey wolf optimizer. All the estimated parameter values were compared with Plett's. The estimation results show that this algorithm can achieve better results than Plett's.

7. REFERENCES

[1] A. Hekmati, "Proposed FEM-Based Optimization Method for Economical Design of Long Permanent-Magnet Guideways With Superconductors", *IEEE Transactions on Applied Superconductivity*, vol. 24, no. 2, pp. 27-35, 2013.

[2] C. Alaoui, "Solid-state thermal management for lithium-ion ev batteries," Vehicular Technology, *IEEE Transactions on*, vol. 62, no. 1, pp.98–107, 2013.

[3] Kwak, Minkyu, et al. "Parameter identification and SOC estimation of a battery under the hysteresis effect." *IEEE Transactions on Industrial Electronics* (2019).

[4] M. Einhorn, V. Conte, C. Kral and J. Fleig, "Comparison of electrical battery models using a numerically optimized parameterization method," 2011 *IEEE Vehicle Power and Propulsion Conference*, Chicago, IL, 2011, pp. 1-7.

[5] O. Tremblay, L. Dessaint and A. Dekkiche, "A Generic Battery Model for the Dynamic Simulation of Hybrid Electric Vehicles," 2007 *IEEE Vehicle Power and Propulsion Conference*, Arlington, TX, 2007, pp. 284-289.

[6] J. Brand, Z. Zhang, R.K. Agarwal, Extraction of battery parameters of the equivalent circuit model using a multi-objective genetic algorithm, *J. Power Sources* 247 (2014) 729–737 (Feb).

[7] P. Rong and M. Pedram, "An analytical model for predicting the remaining battery capacity of lithium-ion batteries,"in *Proc. Design, Autom., Test Eur. Conf.*, 2003, pp. 1148–1149.

[8] M. Pedram and Q. Wu, "Design considerations for battery-powered electronics," in*Proc. 36th Design. Autom. Conf.*, 1999, pp. 861–866.

[9] M. Chen and G. A. Rincon-Mora, "Accurate electrical battery model capable of predicting runtime and I-V performance,"*IEEE Trans. Energy Convers.*, vol. 21, no. 2, pp. 504–511, Jun. 2006.

[10] Y. Cao, R. C. Kroeze and P. T. Krein, "Multi-timescale parametric electrical battery model for use in dynamic electric vehicle simulations", *IEEE Trans. Transportation Electrification*, vol. 2, no. 4, 2016.

[11] E. Samadani, S. Farhad, W. Scott, M. Mastali, L.E. Gimenez, M. Fowler, R.A. Fraser, Empirical modeling of lithium-ion batteries based on electrochemical impedance spectroscopy tests, *Electrochim. Acta* 160 (2015) 169–177 (Apr).

[12] G. L. Plett, "Extended kalman filtering for battery management systems of lipb-based hev battery packs: Part 2. modeling and identification," *Journal of power sources*, vol. 134, no. 2, pp. 262–276, 2004.

[13] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," *Journal of Power Sources*, vol. 198, pp. 359–367, 2012.

[14] Robyn A. Jackey, G. L. Plett, M. J. Klein "Parameterization of a Battery Simulation Model Using Numerical Optimization Methods," SAE Paper 2009-01-1381, *SAE International*, Warrendale, PA, 2009.

[15] G. Plett,Battery Management Systems: Battery Modeling(*Artech House* Power Engineering). Norwood, MA, USA: *Artech House*, 2015. [Online]. Available: http://mocha-java.uccs.edu/BMS1/index.html

[16] [Online]. Available: http://mocha-java.uccs.edu/BMS1/CH02/ESCtoolbox.zip

[17] H. Rahimi-Eichi, F. Baronti, and M. Chow, "Online adaptive parameter identification and state of-charge coestimation for lithium-polymer batter cells,"*IEEE Trans. Ind. Electron.*, vol. 61, no. 4, pp. 2053–2061, Apr. 2014.

[18] H. Rahimi-Eichi and M. Chow, "Adaptive parameter identification and state-of-charge estimation of lithium-ion batteries," inProc. 38th Annu. *Conf. IEEE Ind. Electron. Soc.*, Oct. 2012, pp. 4012–4017.

[19] H. Zhang and M. Chow, "On-line PHEV battery hysteresis effect dynamics modeling," IECON 2010 - *36th Annual Conference on IEEE Industrial Electronics Society*, Glendale, AZ, 2010, pp. 1844-1849, doi: 10.1109/IECON.2010.5675395.

[20] Singh, Narinder, and S. B. Singh. "Hybrid algorithm of particle swarm optimization and Grey Wolf optimizer for improving convergence performance." *Journal of Applied Mathematics*2017 (2017).

[21] T. Huria, G. Ludovici, and G. Lutzemberger, "State of charge estimation of high power lithium iron phosphate cells,"*J. Power Sources*, vol. 249, pp. 92–102, 2014.

[22] A. Poullikkas, “Sustainable options for electric vehicle technologies,” *Renew. Sustain. Energy Rev.*, vol. 41, pp. 1277–1287, 2015.