

Article

Nonlinear Dynamic Model for Parameter Estimation of Li-Ion Batteries Using Supply–Demand Algorithm

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Abstract: The parameter extraction of parameters for Li-ion batteries is regarded as a critical topic for assessing the performance of battery energy storage systems (BESSs). The supply–demand algorithm (SDA) is used in this work to identify a storage system’s unknown parameters. The parameter-extracting procedure is represented as a nonlinear optimization task in which the state of charge (SOC) is approximated using nonlinear features related to the battery current and the initial SOC condition. Furthermore, the open-circuit voltage is approximated using the resulting SOC, which is performed in a nonlinear formula, as well. When used in the dynamic nonlinear BESS model, the SDA was used to verify the fitness values and standard deviation error. Furthermore, the results that were acquired using SDA are compared to recently developed approaches, which are the gradient-based, tuna swarm, jellyfish, heap-based, and forensic-based optimizers. Simulated studies were paired with experiments for the 40 Ah Kokam Li-ion battery and the ARTEMIS driving-cycle pattern. The numerical outcomes showed that the proposed SDA is an approach which is excellent at identifying the parameters. Furthermore, when compared to the other current optimization techniques, for both the Kokam Li-ion batteries and the ARTEMIS drive-cycle pattern, the suggested SDA exhibited substantial precision.

Keywords: dynamic nonlinear model; Li-ion batteries; open-circuit voltage relationship; SOC estimation; supply–demand algorithm



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1. Introduction

The electrical power demand is rapidly increasing to satisfy all requirements of energy around the world. The gas emissions from traditional power plants, created by the burning of fossil fuels, have an impact on the environment’s equilibrium. In 2012, electrical energy apps accounted for around 32% of the total gas emissions in the United States [1]. In order to power electric vehicles (EVs), a range of battery packs is now provided on global marketplaces. Because of their exceptional qualities and performance, Li-ion batteries are considered a great attractive technology for all battery energy storage systems (BESSs) [2,3]. Lithium batteries have inspired the creation of new research for developing BESS technologies, due to their effective environmental consequences and recycling capabilities [4]. BESSs are now installed independently [5] or integrated with renewable sources, such as photovoltaic energy [6], fuel cells, and wind power [7], to improve the reliability of distribution networks. This integration intends to achieve significant economic gains by optimizing the deployment of BESSs into distribution networks in terms of their location and capacity. BESSs can be used to regulate the load capacity that affects electricity networks.

Recently, the parameter estimation of batteries has become a critical challenge for appropriately modeling these elements on the overall system's functioning. Determining the best appropriate prediction for mimicking the battery is still a burgeoning issue of study [8,9]. The determination of battery parameters for the different modeling forms is done by using experimental approaches. The estimation of the SOC is a critical requirement for achieving the appropriate supervision and control of battery charging and discharging [10]. Furthermore, a precise prediction of the battery's characteristics and SOC is critical for a variety of reasons, including increasing the battery's life, regulating the battery's state of charge, enhancing battery performance [11], optimizing energy management, and monitoring battery safety [12]. However, this estimating approach has various drawbacks, including its expense, higher computing capacity, and time consumption, due to the presence of recurrent computing activities. Several linear and non-linear models were presented in Ref. [13]. In Ref. [14], a novel strategy for algorithmic machine learning was suggested to dynamically identify the structure–composition–property connections of the perovskite oxide materials of fuel cells.

Numerous attempts have been performed to determine the best battery settings and derive the charge status. Reference [15] uses a genetic optimization technique to adjust the characteristics of the lithium-ion polymer. Despite the high precision of the genetic optimizer, it has a significant computational cost when compared to the current algorithms, and its performance is largely sensitive to mutation and crossover coefficient settings. For identifying the battery parameters and evaluating the SOC of lithium-ion batteries, the sunflower optimization technique was created [16]. State-space modeling was implemented in the mentioned approach, and the SOC with a battery–voltage relationship was represented by a linear model, but these models are not the situation in practice. Model-based techniques are extensively studied, particularly for a SOC assessment [17]. The analogous circuit-based online extraction of the SOC provides great robustness and accuracy [18]. The acceptable temperature region for LIBs is normally $-20\text{ }^{\circ}\text{C}$ – $60\text{ }^{\circ}\text{C}$. Both low and high temperatures that are outside of this region, however, will lead to a degradation of performance and irreversible damage, such as lithium plating and thermal runaway. The state of charge, which is defined as the ratio of the present capacity to the overall available capacity, can decrease by 23% when the temperature is decreased from $25\text{ }^{\circ}\text{C}$ to $-15\text{ }^{\circ}\text{C}$ [19]. In ref. [20], it has been shown that high temperatures affect the capacity of the battery by 7.5% at $85\text{ }^{\circ}\text{C}$ and 22% at $120\text{ }^{\circ}\text{C}$.

In refs. [21,22], the open-circuit voltage was used to estimate the SOC for lithium batteries by using an approximated linear correlation. This correlation expresses the open-circuit voltage in terms of the state of charge. Since the capacity and materials of the batteries affect this relation, it changes from one pack to the next. Another method for estimating the lithium batteries' state of charge was to use the ampere-hour count process [23]. Whenever the original SOC is available, this process can provide an estimate. Furthermore, because the capacity of the battery is significantly affected by its lifetime [24], it would not be treated as constant. In the last ten years, a large number of studies have focused on estimating the SOC of Li-ion batteries. When designing the parameterization issue, the dynamic model is taken into account. However, in prior estimating-method research, the rate of change in battery parameters was not considered. The change in the rate of the estimated parameters was examined in [25]. Intelligent computational techniques have become a strong option for the SOC estimate of lithium BESSs as numerical algorithms have progressed.

The artificial intelligence (AI) techniques can be used with different estimation approaches, such as the model-based procedure reported in [26], which uses an artificial neural network (ANN) and a nonlinear observation to achieve an effective estimate of the SOC. In ref. [27], a load-classifying ANN was used to categorize the battery operations based on their characteristics, and three ANNs were constructed and trained simultaneously. However, AI technologies necessitate a huge amount of memory in order to retain massive amounts of data, which is not always possible. A model for evaluating and assessing battery packs linked in a series to the system was described in [28]. The evaluation

methodology is built on the basis of real-world operation records. In ref. [29], the aging issue of battery assessment was addressed through a gradual capacity investigation using a radial-training strategy and ANN. The electrochemical energy, based on the integrated procedure storage systems, is described in ref. [30].

The preceding survey characterizes the significant attempts made to assess the parameters reliably and consistently for BESSs, based on Li-ion batteries. Even though these approaches have produced respectable results, the techniques currently proposed in the literature have failed to provide an accurate estimate of the battery's parameters. As a result, this paper provides an optimizer, known as the supply–demand algorithm (SDA) [31], to be developed. It has minimal parameterized settings to alter and is easy to apply. Additionally, the SDA adds the distinguishing features of exploratory and exploitative strategies, which are discriminated by controlling the supply and demand weights. The SDA has been applied effectively for different engineering optimization tasks, such as the performance evaluation of the proton-exchange membrane fuel cells [32], the sizing of hybrid energy systems [33], the photovoltaic cells' design [34], and parameter estimations of an induction motor [35].

Therefore, the SDA is employed for estimating the electrical characteristics of BESSs based on Li-ion batteries. Applications on two benchmarking case studies were carried out to check the capability of the proposed SDA on the nonlinear dynamic model, which were the Li-ion batteries and the ARTEMIS driving-cycle pattern. Furthermore, the results acquired using the SDA were compared to recently developed approaches, such as the gradient-based algorithm (GBA) [36,37], tuna swarm algorithm (TSA) [38], jellyfish algorithm (JFA) [39], heap-based algorithm (HBA) [40] and forensic-based investigation optimizer (FBIA) [41,42]. Efficient and robust parameters were obtained in both cases studied that proved the high closeness between the experimental and estimated performances.

The following is how the remaining portions are organized: Section 2 gives an optimization formulation of the problem of the dynamic nonlinear model of BESSs. Section 3 introduces the SDA. The simulation results are provided in Section 4. Section 5 summarizes the key results of this research, as well as potential future expansions.

2. Problem Formulation

2.1. Modeling of Li-Ion Batteries

Various battery models have been examined in the literature based on the degree of precision desired and the practical use, including electric vehicles. In its corresponding circuit, an efficient dynamic model with two components, the resistance and capacitor (RC), was presented [43]. The n-RC model [44] is a frequently utilized circuit framework for Li-ion batteries, consisting of parallel RC branching, which is linked in series for n times. The corresponding circuit, shown in Figure 1, is a simplified form with two RC branches.

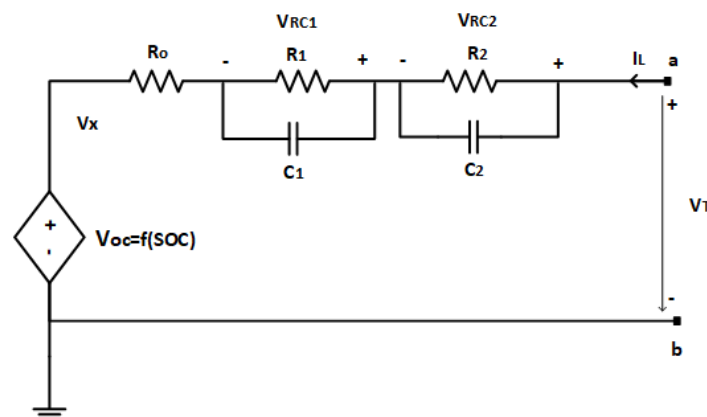


Figure 1. Equivalent circuit model for Li-ion battery.

As shown, V_{oc} and V_T represent, respectively, the open-circuit voltage and terminal voltages of the battery; C_1 and C_2 are, accordingly, the polarized capacitors; R_o indicates the ohmic resistance, while R_1 and R refer to, respectively, the polarized resistors. The relaxing effect is represented by the RC components. To tackle the parameter identifying the SOC estimating challenges, we applied the state-space model. Equation (1) presents the state-space model of the batteries' behavior as follows:

$$\dot{X} = AX + Bu \quad (1)$$

$$y = CX + Du + b_o \quad (2)$$

where

$$X = \begin{bmatrix} SOC \\ V_{RC1} \\ V_{RC2} \end{bmatrix} \quad (3)$$

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{-1}{R_1 C_1} & 0 \\ 0 & 0 & \frac{-1}{R_2 C_2} \end{bmatrix}, B = \begin{bmatrix} \frac{1}{Q_R} \\ \frac{1}{C_1} \\ \frac{1}{C_2} \end{bmatrix}, C = [1 \quad 1 \quad 1], D = [R_o] \quad (4)$$

Whereas a linear association among V_{oc} and SOC was expected to simply reflect the static characteristics of the batteries at a specified temperature and aging conditions [45]; such a relation is intrinsically nonlinear and may be represented using a polynomial-exponential curve [13], as follows:

$$V_{oc} = f(SOC) = \omega_0 + \omega_1 e^{\omega_2(1-SOC)} + \omega_3 e^{\omega_4 SOC} + \omega_5 e^{\omega_6(1-SOC)^2} + \omega_7 e^{\omega_8 SOC^2} + \omega_9 e^{\omega_{10}(1-SOC)^3} + \omega_{11} e^{\omega_{12} SOC^3} \quad (5)$$

where $w_0, w_1, \dots, w_{12}$ are the specified coefficients.

From Equation (5), 13 design coefficients are required to be specified. In addition, the SOC is approximated by utilizing a nonlinear correlation, indicated by Equations (1) and (2), with the battery current (I_b), and taking the starting SOC condition into consideration. It might be calculated using Equation (6) as

$$SOC = 100 \cdot (SOC_o - \frac{1}{Q_b} \int \eta_b I_b dt) \quad (6)$$

where η_b denotes the battery efficiency; SOC_o indicates the starting SOC condition.

2.2. Parameterization Problem of Li-Ion Batteries via Objectives and Constraints

The prior part's dynamic modeling of batteries is used to optimize the parameters of the Li-ion batteries. An optimization model is created to fit the predicted output voltages with the relevant recorded voltages in the experiments. As an objective metric, the sum of squares error (SSE) between the experimental points and estimated ones is minimized. This formation of optimization is typically represented as

$$\begin{aligned} &MOG = \text{Min}_U(G_k(U)), \quad k = 1, 2, \dots, N_{ob} \\ &s.t \\ &U_{Lower} \leq U \leq U_{upper} \end{aligned} \quad (7)$$

MOG denotes a multi-objective expression. Each objective function is represented by G , and its number is N_{ob} . U denotes the controlling BESS variables. The bounds of the BESS variables are denoted as U_{upper} and U_{Lower} . The experimental battery records are used to determine the parameters' extracting methodology. The experimental battery records are utilized to find the extracted parameters. The MOG seeks to minimize the aggregate

of the root mean square difference between the expected and actual state of charge and battery voltage.

$$MOG = \alpha_1 G_1(U) + \alpha_2 G_2(U) \quad (8)$$

where α_1 and α_2 are the weight coefficients which are set to combine the following objectives:

$$G_1(U) = \frac{\sum_{j=1}^{N_{\text{exp}}} (SOC_{\text{exp}} - SOC_{\text{est}})^2}{N_{\text{exp}}} \quad (9)$$

$$G_2(U) = \frac{\sum_{j=1}^{N_{\text{exp}}} (V_{b,\text{exp}} - V_{b,\text{est}})^2}{N_{\text{exp}}} \quad (10)$$

where SOC_{exp} and SOC_{est} are, respectively, the experimental and estimated state of charges. $V_{b,\text{exp}}$ and $V_{b,\text{est}}$ are, respectively, the experimental and estimated battery voltages, whereas the experimental data number is defined by N_{exp} .

Furthermore, the parameters of the BESS are kept within their acceptable limits as follows:

$$R_{o,\text{Lower}} \leq R_o \leq R_{o,\text{upper}} \quad (11)$$

$$R_{j,\text{Lower}} \leq R_j \leq R_{j,\text{upper}} \quad j = 1 \text{ \& } 2 \quad (12)$$

$$C_{j,\text{Lower}} \leq C_j \leq C_{j,\text{upper}} \quad j = 1 \text{ \& } 2 \quad (13)$$

$$Q_{b,\text{Lower}} \leq Q_b \leq Q_{b,\text{upper}} \quad (14)$$

$$w_{j,\text{Lower}} \leq w_j \leq w_{j,\text{upper}} \quad j = 0, 1, 2, \dots, 12 \quad (15)$$

3. SDA for Optimized Parameters Extraction of BESSs Based on Li-Ion Batteries

There are two mechanisms in the SDA. The first is the stability phase. When the market supply (MS) exceeds the market demand (MD), the fluctuations are lessened each time [31]. As a result, the curve of the product supply and price versus time continues to spiral inward. After a fixed number of repetitions, the supply and price settle to the market equilibrium (u_0, v_0). The other mechanism is the instability condition, which occurs when the market supply (MS) is less than the market demand (MD). As a result, the fluctuations will rise each time. Consequently, the curve of the product supply and price versus time continues to spiral outward. As a result, the production and prices deviate further from the market equilibrium (u_0, v_0) over time.

In the SDA, m symbolizes the markets, while every market includes p_s divisions of the diverse products, with every market having a specific amount and price. Every option solution is expressed as the variables by product prices (U), whereas the product amounts (V) are altered as a likely option. As a result, when the contender solution outperforms the previous one, it takes its place. The matrices of the product price and amount may be represented as shown as follows:

$$U = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_m \end{bmatrix} = \begin{bmatrix} u_1^1 & u_1^2 & \cdots & u_1^{p_s} \\ u_2^1 & u_2^2 & \cdots & u_2^{p_s} \\ \vdots & \vdots & \vdots & \vdots \\ u_m^1 & u_m^2 & \cdots & u_m^{p_s} \end{bmatrix} \quad (16)$$

$$V = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} = \begin{bmatrix} v_1^1 & v_1^2 & \cdots & v_1^{p_s} \\ v_2^1 & v_2^2 & \cdots & v_2^{p_s} \\ \vdots & \vdots & \vdots & \vdots \\ v_m^1 & v_m^2 & \cdots & v_m^{p_s} \end{bmatrix} \quad (17)$$

where u_i ($i = 1: p_s$) and v_i ($i = 1: p_s$) are the i^{th} vector of the product price and quantity that are significant to a possible solution; m denotes the number of marketplaces; j denotes the control parameters within every vector; p_s represents its dimensionality. The fitness score is used to evaluate the two product vectors of the product and price from every marketplace. As a result, an array may be created based on the fitness scores of the vectors of the product price and product within every market, which are denoted in Equations (18) and (19).

$$Fu = [Fu_1 \quad Fu_2 \quad \cdots \quad Fu_m]^T \quad (18)$$

$$Fv = [Fv_1 \quad Fv_2 \quad \cdots \quad Fv_m]^T \quad (19)$$

The vector of the equilibrium product (u_0) is evaluated as:

$$N_j = \left| Fv_j - \frac{1}{m} \sum_{j=1}^m Fv_j \right| \quad (20)$$

$$Q = \frac{N_j}{\sum_{j=1}^m N_j} \quad (21)$$

$$v_0 = v_k, \quad k = \text{RWS}(Q) \quad (22)$$

where *RWS* is the roulette-wheel selection.

The vector of equilibrium price (u_0) is evaluated as:

$$M_j = \left| Fu_j - \frac{1}{m} \sum_{j=1}^m Fu_j \right| \quad (23)$$

$$P = \frac{M_j}{\sum_{j=1}^m M_j} \quad (24)$$

$$u_0 = \begin{cases} Ra \cdot \frac{\sum_{i=1}^n x_i}{m} & \text{if } r_a < 0.5 \\ x_k, k = \text{RWS}(P) & r_a \geq 0.5 \end{cases} \quad (25)$$

where *Ra* is a randomized integer between [0,1]. Depending on its likelihood in the vector of the equilibrium price via the price array, the SDA estimates that there is a 50% possibility of picking between the mean price and the current vectors in Equation (25). The supply and demand equations within every market could perhaps be adjusted correspondingly, as indicated in Equations (26) and (27), accordingly, by defining the equilibrium price (u_0) and product (v_0) vectors:

$$v_i(t+1) = v_0 + \alpha \cdot (u_i(t) - u_0) \quad (26)$$

$$u_i(t+1) = u_0 - \beta \cdot (v_i(t+1) - v_0) \quad (27)$$

where $u_i(t)$ is the vector of the i^{th} product price at period t and $v_i(t)$ is the vector of the i^{th} product amount at period t . The demand and supply ratios are represented by β and α , respectively. Therefore, the formula may be rewritten as:

$$u_i(t+1) = u_0 - \alpha\beta \cdot (u_i(t) - u_0) \quad (28)$$

where

$$\alpha = \frac{2 \cdot (T - t + 1)}{T} \cdot \sin(2\pi r) \quad (29)$$

$$\beta = 2 \cdot \cos(2\pi r) \quad (30)$$

where T is the number of iterations and r denotes a randomized integer from the range $[0,1]$.

Correlation between the Algorithm Model and the Parameters Estimation of BESSs Research

The key stages of the SDA to handle the effective and practical parameters of BESSs, based on the Li-ion batteries with a nonlinear dynamic model, are represented in Figure 2. As seen, the SDA is straightforward to deploy and simply requires a few settings to be altered. Its temporal context is governed by the number of markets, the dimensionality of the task, the maximum iteration, the RWS, the number of commodities, and the price adjustments within every iteration. As a result, the SDA gives distinguishing exploratory and exploitative features by altering the demand and supply ratios α and β . The phases of the SDA implementation for estimating the optimum BESS variables are as follows:

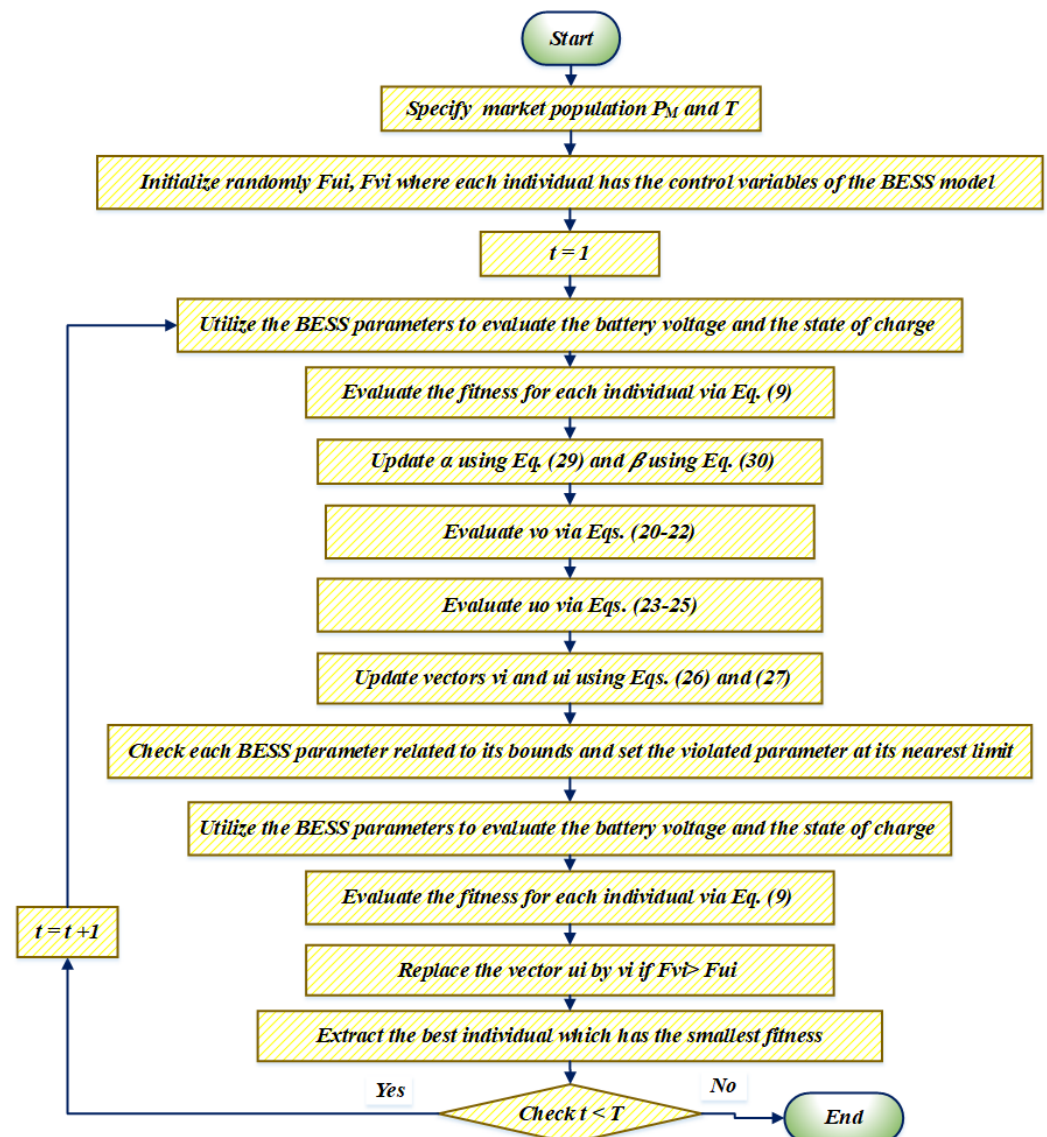


Figure 2. Main steps of SDA for effective and practical parameters of BESSs.

Step 1: Import the experimental data from the investigated BESS.

Step 2: Establish the population size, maximal iterations number and bounds of the independent variables. The BESS parameters, which are produced by a randomized strategy inside the required bounds, reflect the original members of the commodities' quantity and price directions. The size of the population determines the number of commodity prices and quantity vectors.

Step 3: The BESS parameters determine the output voltage and state of charge.

Step 4: The fitness function is computed based on the RMSE model, as in Equation (9).

Step 5: The SDA's updating system, as explained in the preceding part, is enabled to refresh the commodities' quantity and price vectors.

Step 6: Every BESS attribute is checked against its boundaries, and any violating variable is adjusted to its closest boundary, which ensures that the inequality requirements associated with the control variables are met and that they are always inside the search space under consideration.

Step 7: After running the maximal iterations number, the best participant is retrieved and modified to be the optimal BESS parameters.

4. Simulation Results

Inside this section, the 40 Ah Li-ion battery cell is an example of a commercial battery that achieves significant increases in driving performance and dependability. Its specification has the following characteristics: nominal voltage rating is 3.7 V, capacity is 40 Ah, intrinsic resistance is 0.9 m Ω , both charging and discharging currents are 40 amperes, and the specific energy is 167 Wh/kg of weight 0.885 kg [46]. The recommended estimation technique, implemented for the Artemis driving cycle, is provided. Additionally, the GBA, JFA, TSA, HBA, and FBIA were implemented as well. The simulation studies were executed with the same number of iterations with 500 and the individuals' number of 100.

4.1. Simulation Results of Li-Ion Battery Cell

Table 1 presents the considered boundaries of the estimated parameters of the Li-ion battery cells [16]. As shown, the number of the control variables is high, with 20 parameters, where the relation between the VOC and SOC is taken in its high nonlinear form. For the experimental and estimated values, the competitive algorithms: SDA, GBA, JFA, TSA, HBA and FBIA are applied. Table 2 displays their optimal fitness function and the associated improvements, compared to the obtained results by the proposed SDA. The detailed optimal BESS parameters are tabulated in the Appendix A and relate to all the implemented techniques (Table A1). In addition, Figure 3 displays the corresponding convergence characteristics of the SDA versus the other techniques for the Li-ion battery cell parameters.

Table 1. Boundaries for Li-ion battery cell parameters.

Parameter	Lower Bound	Upper Bound
R_o (Ω)	0.010	0.010
R_1 (Ω)	0.000	1.300
C_1 (mF)	0.000	0.105
R_2 (Ω)	0.000	1.300
C_2 (mF)	0.000	0.105
Q_b (A.s)	13,000.0	170,000.0
$\omega_0, \omega_1, \dots, \omega_{12}$	−100.00	100.00

Table 2. Comparative results for Li-ion battery cell parameters.

Items	SDA (2019)	GBA (2020)	JFA (2021)	TSA (2021)	HBA (2020)	FBIA (2020)
RMSE	8.0200×10^{-3}	8.1930×10^{-3}	9.1640×10^{-3}	8.2240×10^{-3}	9.2670×10^{-3}	9.2160×10^{-3}
RMSE % Improvement	-	2.157	14.264	2.5436	15.5486	14.9127

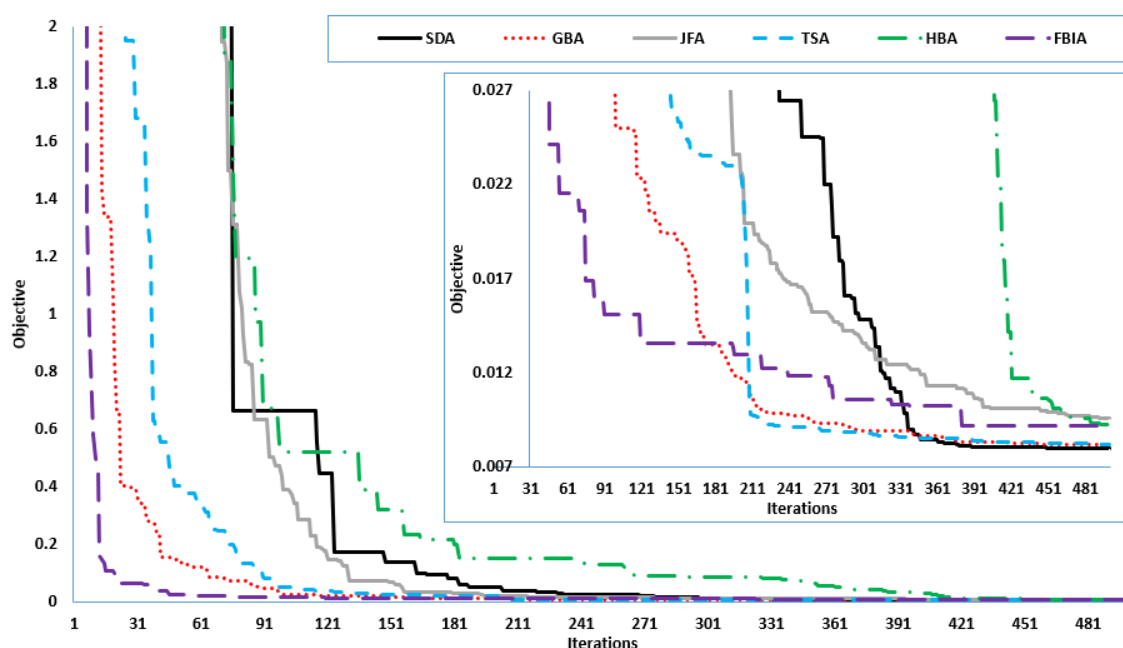


Figure 3. Convergence characteristics of SDA versus other techniques for Li-ion battery cell parameters and the related zoomed portion with smallest objective value.

From Table 2 and Figure 3, the SDA finds the minimum objective value of 0.00802. On the other side, the GBA, JFA, TSA, HBA and FBIA achieve counterpart objective values of 0.008193, 0.009164, 0.008224, 0.009267 and 0.009216, respectively. The essential difference between the main Figure 3 and the small inserted figure is that the inserted portion represents a zooming focus on the small RMSE values. Figure 3 displays that the SDA requires more iterations before approaching the stable zone, compared to the GBA and TSA. The proposed SDA provides the least value of the considered objective. The improvement in the RMSE is recorded in the last row between the proposed SDA and the other compared algorithms. As shown, the proposed SDA provides a great improvement with 14.264, 15.5486 and 14.9127% compared to the JFA (2021), HBA (2020) and FBIA (2020), respectively. Added to that, the proposed SDA shows an improvement of 2.157% and 2.5436% compared to the GBA (2020) and TSA (2021), respectively. Therefore, the proposed SDA outperformed the others.

For the Li-ion battery cell, Figure 4 describes the whiskers boxplot for the compared algorithms of SDA, GBA, JFA, TSA, HBA and FBIA. As shown, the best performance is accompanied by the SDA and FBIA, since their acquired boxes have very small lengths compared to the others. On the contrary, the worst performance is due to the TSA, which has the highest length of its acquired box. Despite that, the HBA and GBA show the far outlier points of 0.117968077 and 0.118542406, respectively.

As illustrated in Figure 5, the SDA achieves the least indices of the maximum, mean and minimum objective values of 0.011333845, 0.009074044, and 0.008020075, respectively. Secondly, the FBIA achieves little higher indices of the maximum, mean and minimum objective values of 0.013716547, 0.010839514, and 0.009215654, respectively. Based on these indices, the worst maximum value is due to the HBA and GBA, which has the highest objective values of 0.117968077 and 0.118542406, respectively. Nevertheless, Figure 6 depicts the standard deviation comparison for the SDA, GBA, JFA, TSA, HBA and FBIA. As shown, both the SDA and FBIA provide the least area of 1%. With a highly accurate comparison, the acquired standard deviation is 0.001131406, based on the SDA, whilst the acquired standard deviation is 0.035765609, based on the FBIA. This assessment shows the SDA gave a better performance than the FBIA, with more than 30% accuracy. On the other side, the other techniques can be ascendingly ordered as JFA, HBA, GBA and TSA, where they have percentages of 15%, 26%, 28% and 29%, respectively.

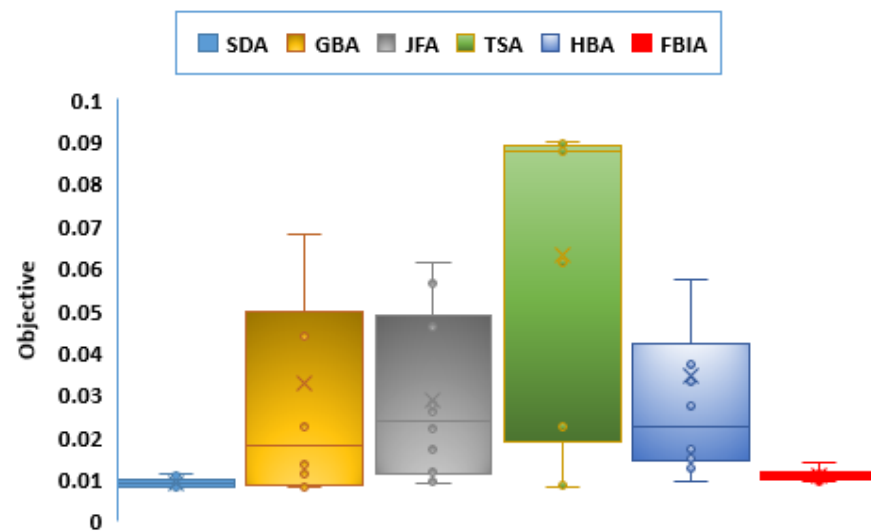


Figure 4. Whiskers boxplot for SDA, GBA, JFA, TSA, HBA and FBIA for Li-ion battery cell parameters.

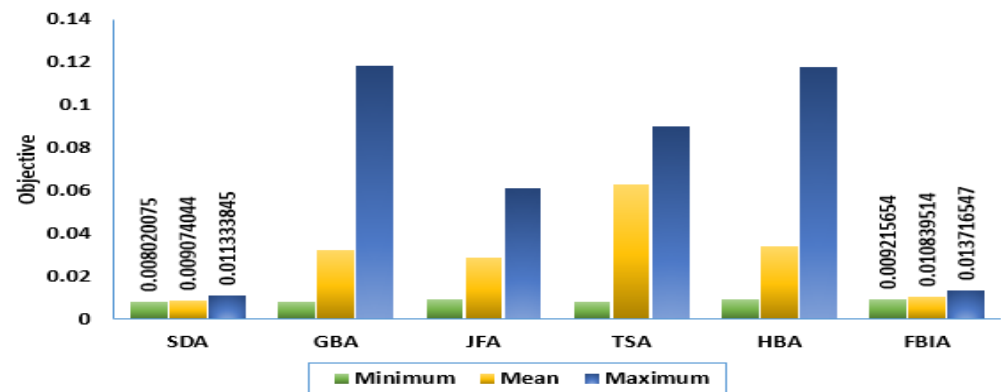


Figure 5. Minimum, mean and maximum objective values for SDA, GBA, JFA, TSA, HBA and FBIA.

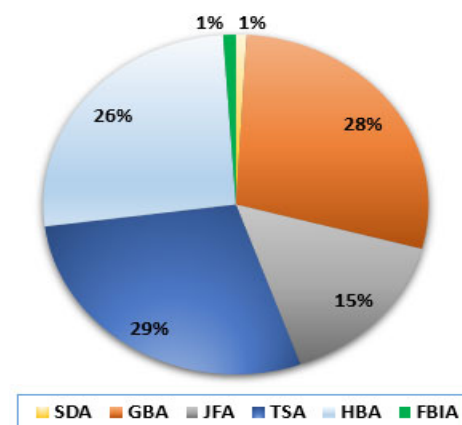


Figure 6. Standard deviation comparison for SDA, GBA, JFA, TSA, HBA and FBIA for Li-ion battery cell parameters.

Otherwise, for the Li-ion battery parameters, Figure 7 displays the related experimental and estimated battery voltage via the SDA. Considering the RMSE as the main objective function, Figure 8 depicts the absolute errors of the estimated voltages via the SDA. From both figures, the great success of the proposed SDA is described between the estimated and experimental voltages, with a trivial average absolute error.

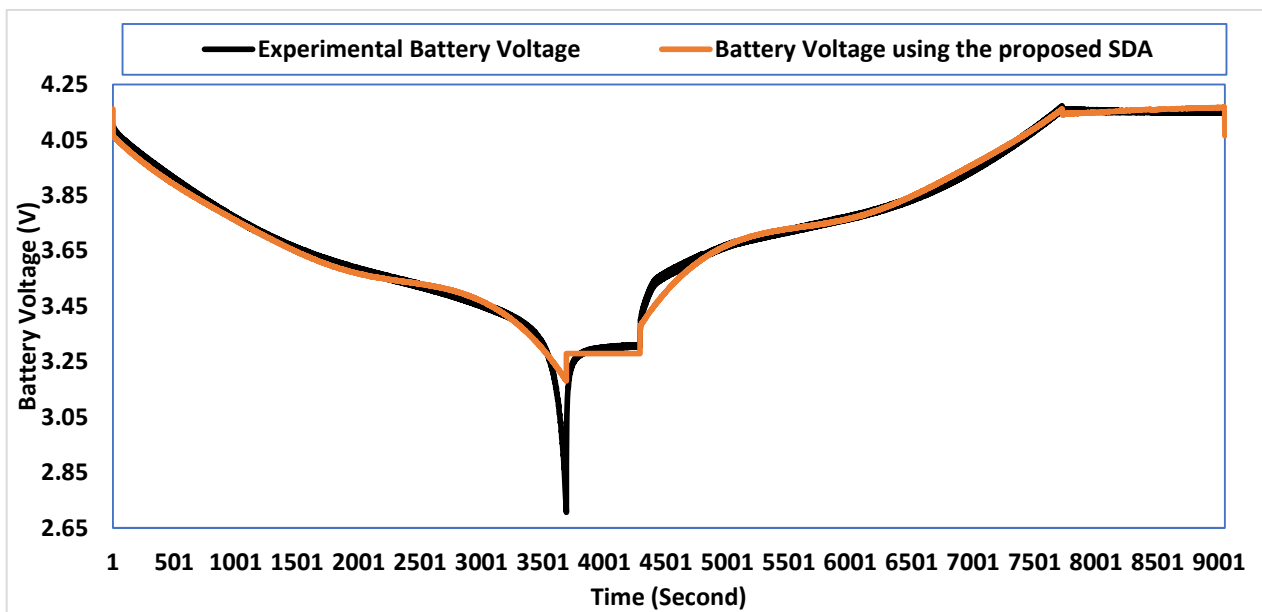


Figure 7. Battery voltage with experimental and approximated values using the SDA for Li-ion battery characteristics.

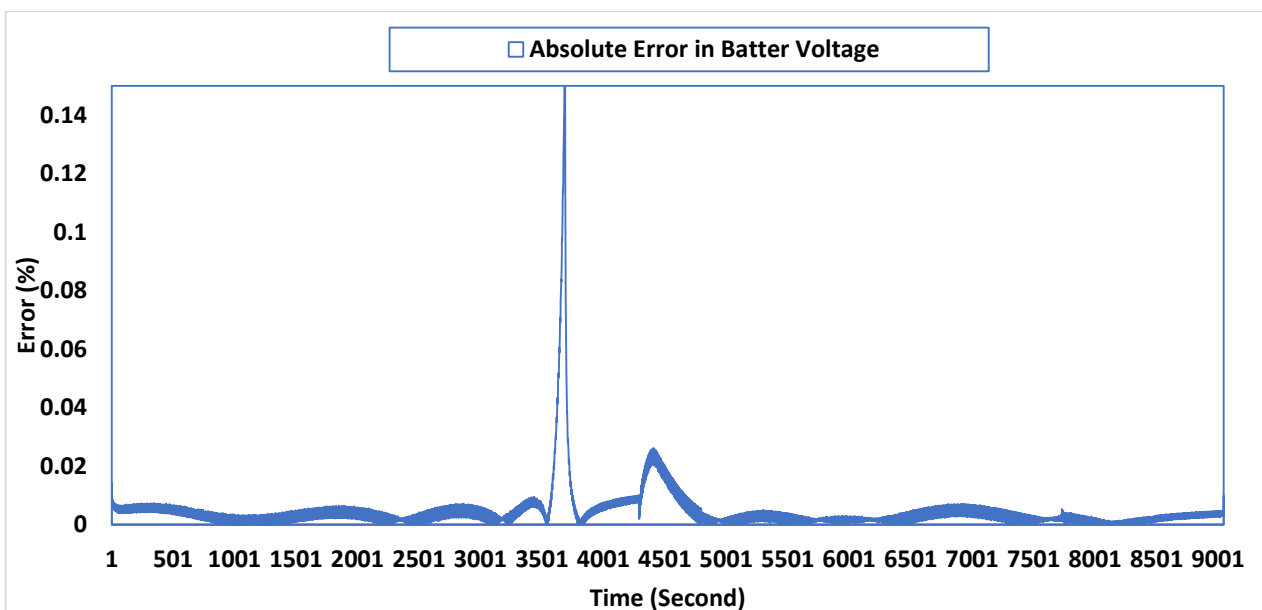


Figure 8. Percentage of the absolute error of the estimated battery voltage for Li-ion batteries using SDA.

Furthermore, Figure 9 shows the experimental and predicted SOC_s for the Li-ion battery properties by using the suggested SDA. The relative inconsistency of the predicted SOC utilizing the indicated SDA for the Li-ion battery properties is also shown in Figure 10. The high success of the suggested SDA is described between the experimental and estimated SOC_s in both figures, since the maximum absolute error does not exceed 0.0006.

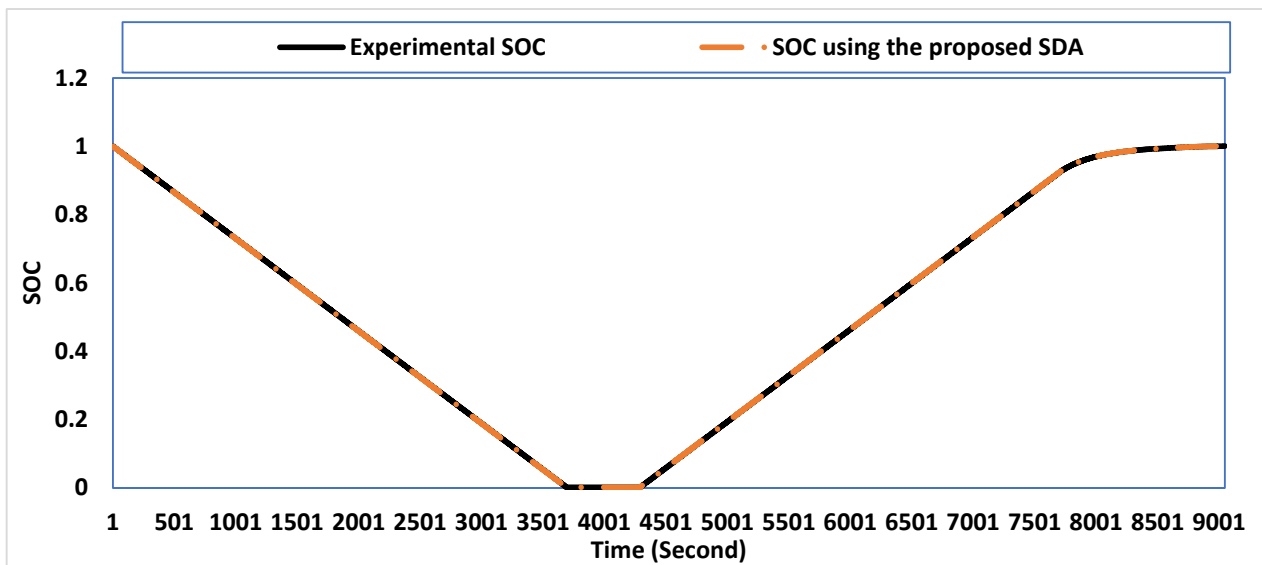


Figure 9. SOC with experimental and approximated values using the SDA for Li-ion battery characteristics.

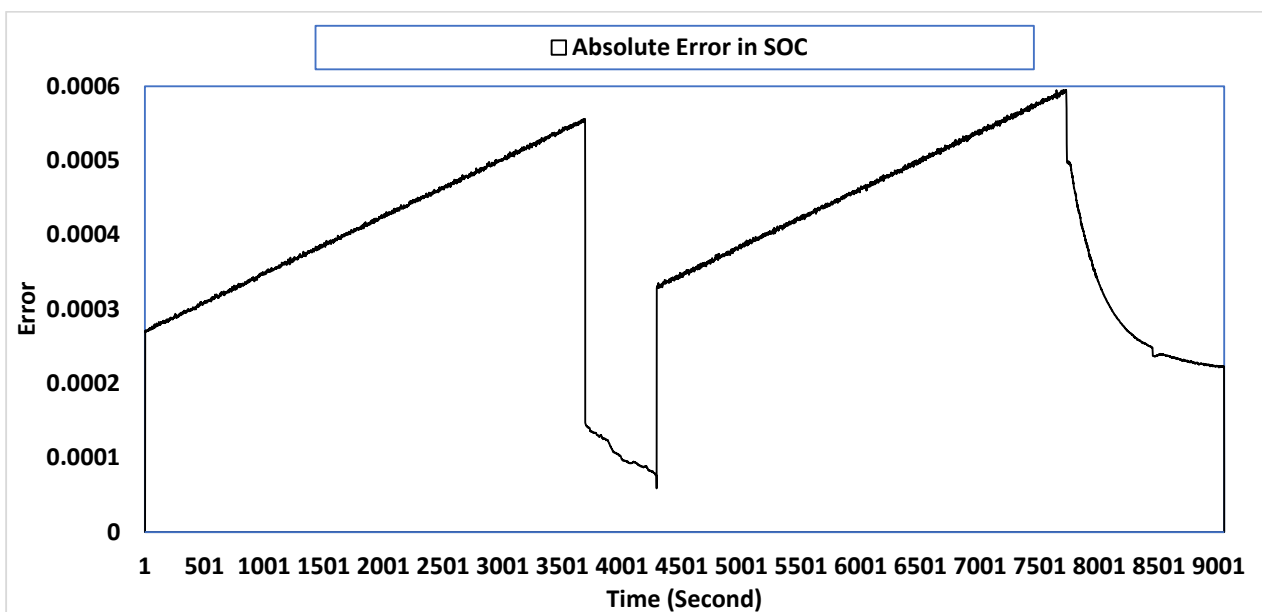


Figure 10. Absolute error of the evaluated SOC for Li-ion batteries using SDA.

4.2. Simulation Results of ARTEMIS Driving Cycle

The ARTEMIS driving cycle is chosen in this portion for collecting the BESS characteristics using the dynamic modeling of an urban electric vehicle (Bolloré Bluecar) [47]. The tested driving cycle is modeled using speed–time sequences that simulate the traffic circumstances and driving behavior in a specified location. The Assessment and Reliability of Transport Emission Models Inventory Systems (ARTEMIS) driving cycle is used in this work to simulate real-world driving behavior.

ARTEMIS is divided into three driving cycles: highway, rural, and urban. This pattern was chosen to reflect the rural and urban rounds. Various types of batteries have recently been created to suit the primary needs of electric and hybrid cars while improving driving performance and dependability, such as a commercial 40 Ah Li-ion battery [16,46].

The ARTEMIS driving cycle was completed in this study by the rural and urban cycle, with a mean distance of 22 km in 2075 s. The regular and maximum speeds were 38.4 and

111.5 km per hour, respectively. The proposed SDA, GBA, JFA, TSA, HBA and FBIA values were utilized for the experimental and estimated values to minimize the accumulation of the root mean square of the normalized variation between the battery voltage and state of charge. Table 3 displays their optimal fitness function. The detailed optimal BESS parameters are tabulated in the Appendix A and relate to all the implemented techniques (Table A2). Furthermore, Figure 11 shows the convergence properties of the SDA versus the other approaches for the ARTEMIS driving cycle.

Table 3. Comparative results for ARTEMIS driving-cycle parameters.

Items	SDA (2019)	GBA (2020)	JFA (2021)	TSA (2021)	HBA (2020)	FBIA (2020)
RMSE	4.4116×10^{-3}	4.4485×10^{-3}	4.4818×10^{-3}	4.4877×10^{-3}	4.6836×10^{-3}	5.0492×10^{-3}

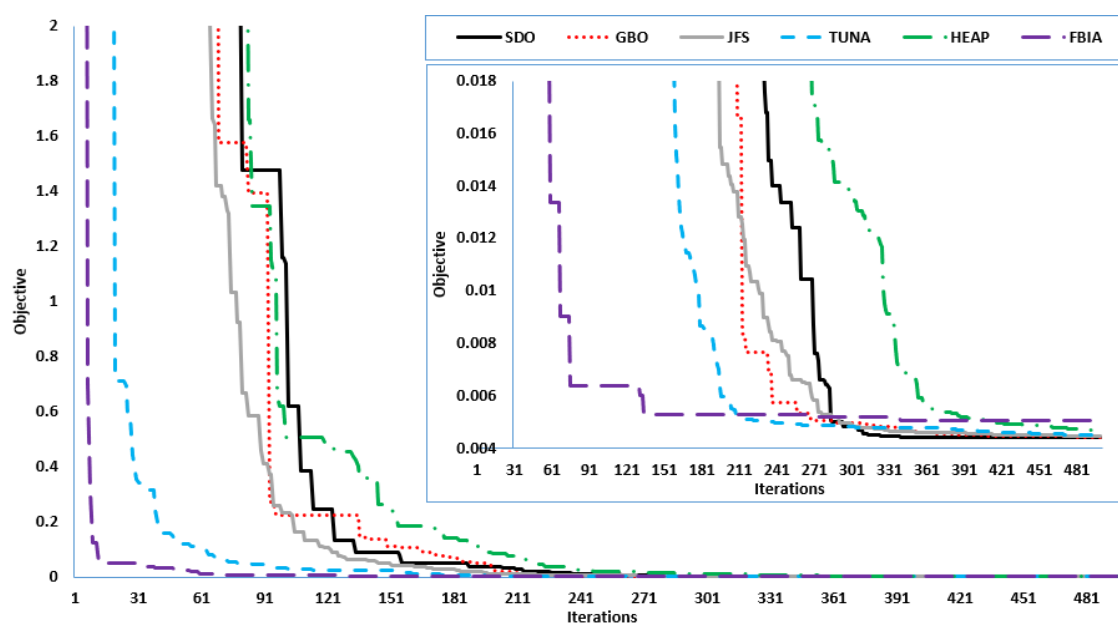


Figure 11. Convergence characteristics of SDA versus other techniques for ARTEMIS driving cycle and the related zoomed portion with smallest objective value.

Table 3 and Figure 11 show that the SDA outperformed the others since it found the minimum objective value of 0.004411594. On the other side, the GBA, JFA, TSA, HBA and FBIA achieved the counterpart objective values of 0.004448455, 0.004481826, 0.004487704, 0.00468358 and 0.005049191, respectively.

For the ARTEMIS driving cycle, Figure 12 describes the whiskers boxplot for the comparison algorithms of SDA, GBA, JFA, TSA, HBA and FBIA. As shown, the best performance was accompanied by the SDA, whereas the worst performance was due to the TSA. Figure 13 describes the minimum, mean and maximum objective values for SDA, GBA, JFA, TSA, HBA and FBIA. As shown, the compared techniques can be ascendingly ordered for each index. Based on the minimum objective, the SDA achieved the least minimum objective value of 0.004411594, whereas the GBA, JFA, TSA, HBA and FBIA came sequentially. Based on the mean objective, the SDA achieved the least value of 0.004730328, whereas the GBA, FBIA, HBA, JFA and TSA came sequentially with the values of 0.005008, 0.005652, 0.008292, 0.01169 and 0.027305, respectively. Based on the maximum objective, the SDA achieved the least minimum objective value of 0.005318936, whereas the FBIA, GBA, HBA, JFA and TSA came sequentially with the values of 0.006576, 0.007183, 0.017607, 0.024234 and 0.053627, respectively.

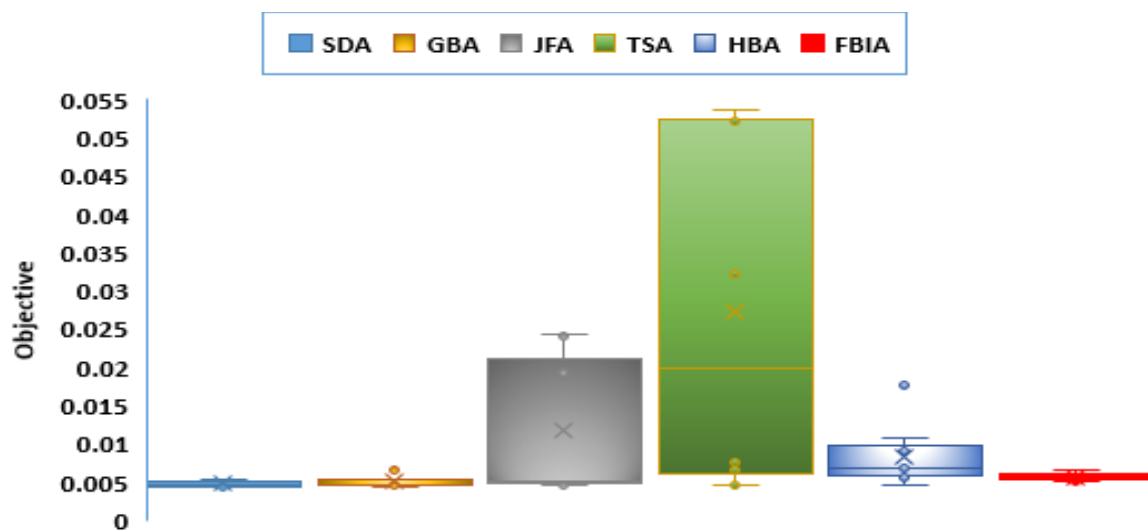


Figure 12. Whiskers boxplot for SDA, GBA, JFA, TSA, HBA and FBIA for ARTEMIS driving cycle.

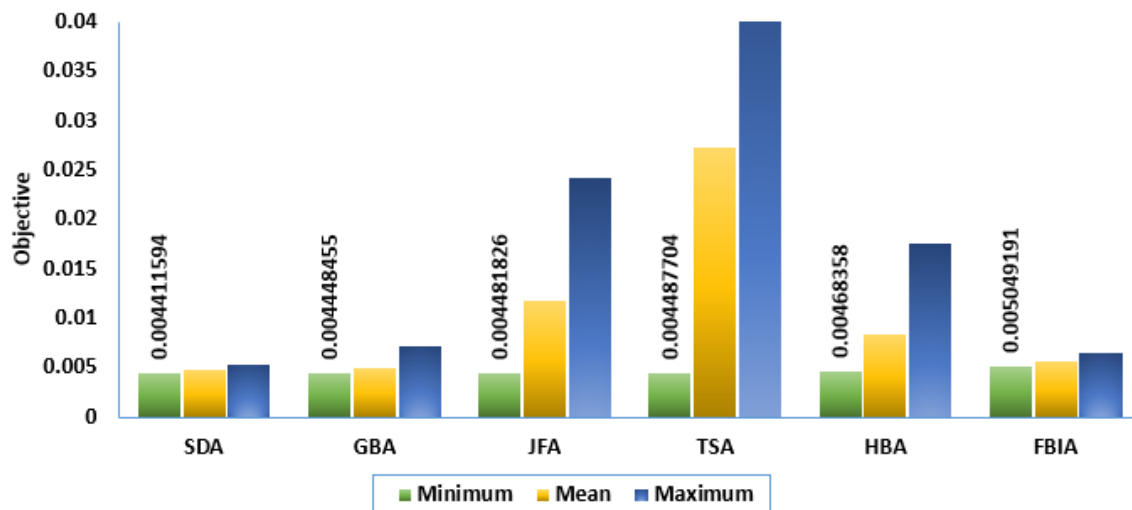


Figure 13. Minimum, mean and maximum objective values for SDA, GBA, JFA, TSA, HBA and FBIA for ARTEMIS driving cycle.

Nevertheless, Figure 14 depicts the standard deviation comparison for the SDA, GBA, JFA, TSA, HBA and FBIA. As shown, both the SDA and FBIA provide the least area of 1%. With a highly accurate comparison, the acquired standard deviation is 0.000307, based on the SDA, whilst the acquired standard deviation is 0.000489, based on the FBIA. This assessment shows the SDA gave a better performance than the FBIA. On the other side, the other techniques can be ascendingly ordered as GBA, HBA, JFA and TSA, where they have percentages of 3%, 10%, 24% and 61%, respectively, where the obtained standard deviations are 0.001013, 0.003797, 0.008961 and 0.023203, respectively.

Similarly, Figure 15 shows the experimental and projected battery voltages for the ARTEMIS driving cycle using the suggested SDA, while Figure 16 describes the related current profile. In addition, Figure 17 shows the absolute inaccuracy of the projected battery voltage via the SDA for the ARTEMIS driving cycle. The significant success of the suggested SDA is presented between the experimental and estimated voltages in both figures since the highest absolute error does not exceed 0.02 percent. In addition, Figure 18 depicts the predicted and experimental SOC during the ARTEMIS driving cycle using the proposed SDA. The absolute error of the anticipated SOC utilizing the suggested SDA for the ARTEMIS driving cycle is also shown in Figure 19. Because the highest absolute error

does not exceed 0.00014, the substantial effect of the prescribed SDA is reflected between the experimental and estimated SOC in both figures.

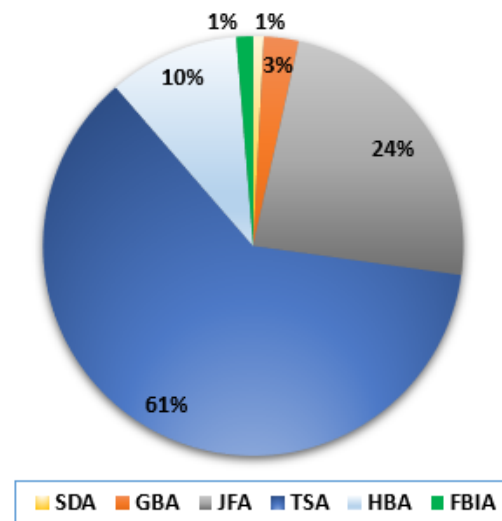


Figure 14. Standard deviation comparison for SDA, GBA, JFA, TSA, HBA and FBIA for ARTEMIS driving cycle.

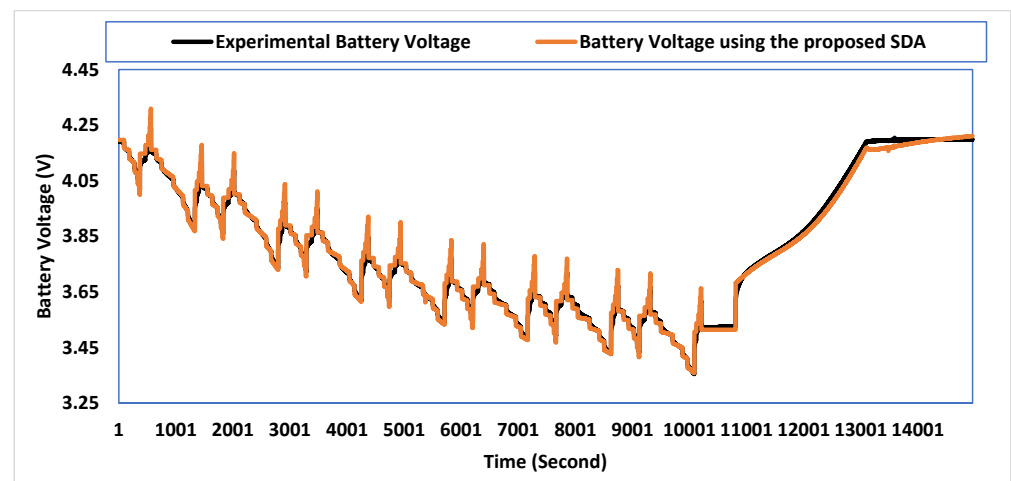


Figure 15. Battery voltage with experimental and approximated values using the SDA for ARTEMIS driving cycle.

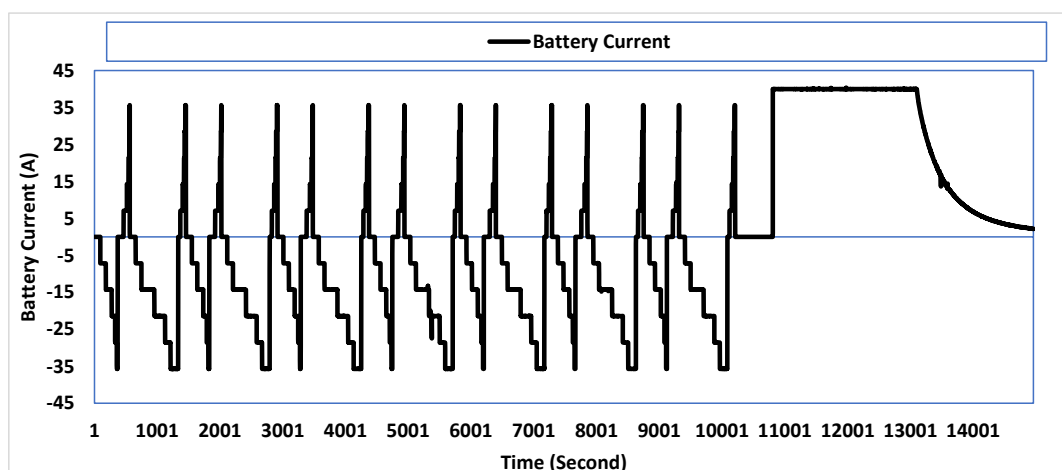


Figure 16. Battery current with experimental values for ARTEMIS driving cycle.

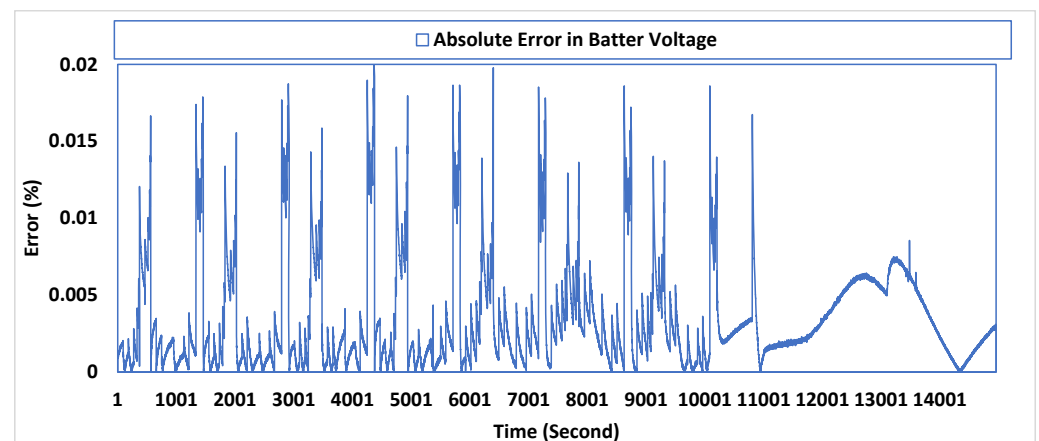


Figure 17. Percentage of the absolute error of the evaluated battery voltage for ARTEMIS driving cycle using SDA.

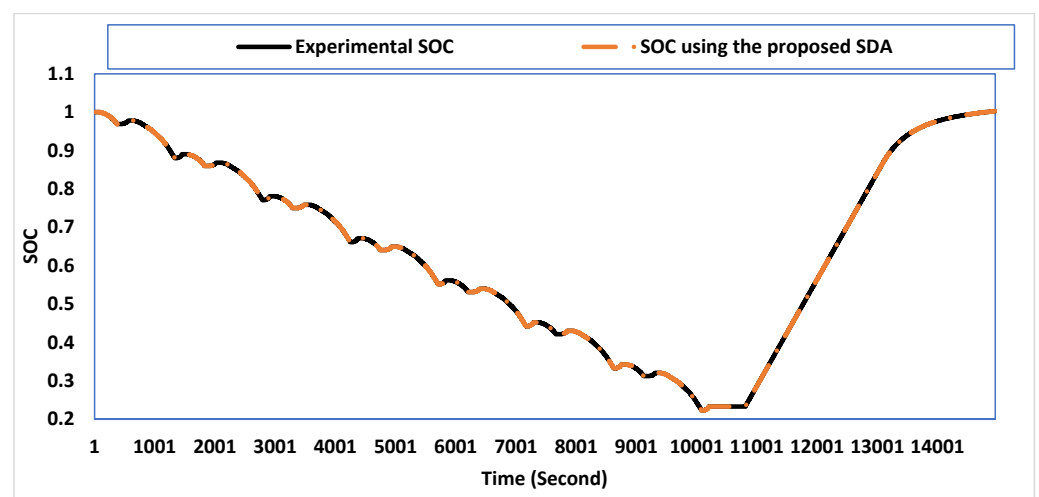


Figure 18. SOC with experimental and approximated values using the SDA for ARTEMIS driving cycle.

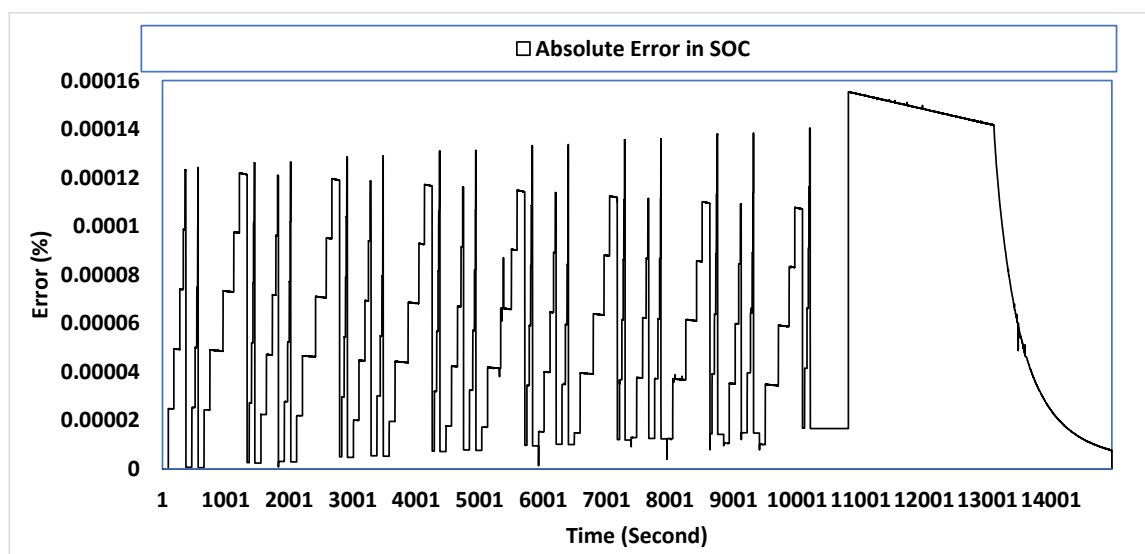


Figure 19. Absolute error of the evaluated SOC for ARTEMIS driving cycle using SDA.

5. Conclusions

The supply–demand-based algorithm (SDA) is used in this study to precisely extract the unidentified practical parameters of BESSs based on Li-ion batteries using a nonlinear dynamic model. The estimate problem is represented as a nonlinear optimization problem where the nonlinear relation between the state of charge (SOC), the battery current and the initial SOC condition is handled, as opposed to previous linear frameworks. Therefore, the solution methodology based on SDA yields a suitable combination between the state-space modeling and nonlinear modeling. The proposed approach is tested on a 40 Ah Kokam Li-ion battery, and a dynamic validation analysis on the ARTEMIS driving cycle is conducted to demonstrate the capacity of the suggested solution technique. The statistical findings indicate the suggested SDA's great capabilities as an efficient identification technique. Furthermore, the suggested SDA exhibits substantial precision when compared to the recently competitive optimizer. For both applications, and considering the minimum mean and maximum fitness function values, the SDA achieves the least levels for these indices compared with the competing algorithms, GBA, JFA, TSA, HBA and FBIA. The limitation of the proposed algorithm, besides all the optimizers, appears in how to deal with the high variations of the battery samples. These variations require special treatment for their response. Thus, for future work, training-based techniques can be merged with advanced optimizers, such as the equilibrium optimizer [48] to alleviate the resulting problems.

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Appendix A

Tables A1 and A2 show the optimal parameter settings of the competing algorithms for the BEESs and ARTEMIS driving cycle, respectively.

Table A1. Optimal parameter settings for BESSs.

Parameters	SDA (2019)	GBA (2020)	JFA (2021)	TSA (2021)	HBA (2020)	FBIA (2020)
R_o	1.1710×10^{-3}	2.2340×10^{-3}	8.9200×10^{-4}	1.0000×10^{-5}	2.3420×10^{-3}	7.1900×10^{-4}
w_0	3.3232	1.2739	3.7625	1.0000	3.6565	2.6351
w_1	6.2810×10^{-2}	-4.3769×10^{-1}	-7.1382×10^{-1}	1.7613×10^{-1}	-1.2956×10^{-1}	-3.8412×10^{-1}
w_2	-2.0443	1.0494	-4.8144	-8.2037	-1.4711×10^1	1.0308
w_3	-8.8259×10^{-1}	1.6589×10^{-2}	-7.2151×10^{-1}	-6.9302×10^{-1}	-2.2919×10^{-1}	9.0911×10^{-2}
w_4	-2.6769	-1.0309	-6.6625	-2.6719	-2.4416×10^1	1.3168×10^{-1}
w_5	1.7661	3.2928	2.4461	2.8413	1.6965	3.6720×10^{-1}
w_6	-5.0608×10^{-1}	-2.6934×10^{-1}	-2.1049×10^1	5.7460×10^{-2}	-2.0319×10^1	-3.3207×10^{-1}
w_7	2.7984×10^{-1}	3.8607	4.9809×10^{-1}	-5.9607×10^{-1}	-1.4680×10^{-2}	7.6205×10^{-1}

Table A1. Cont.

Parameters	SDA (2019)	GBA (2020)	JFA (2021)	TSA (2021)	HBA (2020)	FBIA (2020)
w_8	6.9816×10^{-1}	-7.2076×10^{-1}	-2.1844×10^1	-2.5581×10^1	-5.8492×10^1	3.3634×10^{-1}
w_9	-1.5002	-4.9791×10^{-1}	-1.3831	1.8460×10^{-1}	-1.0924	3.5907×10^{-1}
w_{10}	-2.3231	-1.8237	-9.6681×10^1	-4.4144×10^1	-9.9364×10^1	-3.2747×10^{-1}
w_{11}	-3.6752×10^{-1}	-3.0521	-2.8416×10^{-1}	5.5591×10^{-1}	-1.6626×10^{-1}	3.5590×10^{-1}
w_{12}	-4.9946	-8.0712×10^{-1}	-4.0284×10^1	-1.0000×10^2	-9.9849×10^1	-1.0838×10^1
Q_b	1.4796×10^5	1.4795×10^5	1.4797×10^5	1.4797×10^5	1.4798×10^5	1.4788×10^5
R_1	6.1000×10^{-4}	5.2900×10^{-6}	1.0680×10^{-3}	2.4320×10^{-3}	8.4300×10^{-5}	1.7050×10^{-3}
C_1	5.3538×10^{-2}	1.5400×10^{-4}	2.8489×10^{-2}	1.0000×10^{-6}	8.6245×10^{-2}	5.9723×10^{-2}
R_2	6.8300×10^{-4}	2.5800×10^{-4}	5.1200×10^{-4}	1.0000×10^{-6}	3.3800×10^{-6}	1.6900×10^{-4}
C_2	8.3440×10^{-2}	1.1000×10^{-5}	9.8036×10^{-2}	1.0000×10^{-6}	8.4449×10^{-2}	5.9705×10^{-2}

Table A2. Optimal parameter settings for ARTEMIS driving cycle.

Parameters	SDA (2019)	GBA (2020)	JFA (2021)	TSA (2021)	HBA (2020)	FBIA (2020)
R_o	1.2717×10^{-3}	1.2763×10^{-3}	1.3120×10^{-3}	4.1463×10^{-3}	4.1830×10^{-3}	1.7155×10^{-3}
w_0	3.6865	3.3523	3.6138	3.6542	3.6217	2.9002
w_1	3.3033×10^{-1}	-5.8950×10^{-1}	1.0085×10^{-1}	1.4872×10^{-2}	3.2969×10^{-2}	-3.2351×10^{-2}
w_2	-4.6108	-8.6475×10^{-1}	-1.2181×10^1	-8.4554×10^1	-7.7520×10^1	-2.3522
w_3	-3.4842×10^{-1}	-7.4126×10^{-1}	-9.9131×10^1	-9.3177×10^1	-1.0000×10^2	-2.3466×10^{-1}
w_4	-9.0153	-5.7937×10^{-1}	-3.5919×10^1	-2.5526×10^1	-9.7163×10^1	7.7965×10^{-1}
w_5	3.0028×10^{-1}	1.1688	1.8504×10^{-1}	2.0108×10^{-1}	2.1510×10^{-1}	-2.4032×10^{-1}
w_6	-8.6588	-1.1185	-4.1395×10^1	-9.0805×10^1	-6.4522×10^1	-7.8605×10^{-2}
w_7	-2.1076×10^{-1}	2.7213×10^{-1}	1.9384	2.4972	1.2914×10^1	1.5704
w_8	-8.2188	1.1372	-6.6996×10^1	-4.2175×10^1	-9.9924×10^1	3.9334×10^{-1}
w_9	-1.2480×10^{-1}	-1.6802×10^{-1}	2.8872×10^{-1}	3.1630×10^{-1}	3.2177×10^{-1}	-4.9499×10^{-1}
w_{10}	-2.2433	-1.9211	-1.7442×10^1	-2.7393×10^1	-2.0928×10^1	4.6201×10^{-1}
w_{11}	3.9310×10^{-2}	3.1791×10^{-1}	-2.4682×10^{-1}	-2.0414×10^{-1}	-3.2501×10^{-1}	1.3581×10^{-1}
w_{12}	-3.4717	-7.4593	-5.1422×10^1	-2.3842×10^1	-5.5243×10^1	5.8510×10^{-1}
Q_b	1.4400×10^5	1.4400×10^5	1.4400×10^5	1.4400×10^5	1.4400×10^5	1.4399×10^5
R_1	1.8011×10^{-3}	2.2901×10^{-3}	1.1348×10^{-3}	1.0000×10^{-6}	1.0000×10^{-6}	5.2647×10^{-4}
C_1	6.5384×10^{-2}	8.0927×10^{-2}	2.4314×10^{-2}	1.0000×10^{-1}	1.0000×10^{-6}	2.0985×10^{-2}
R_2	1.1066×10^{-3}	6.0190×10^{-4}	1.7219×10^{-3}	1.0000×10^{-6}	2.1714×10^{-6}	1.8440×10^{-3}
C_2	5.3797×10^{-2}	3.2747×10^{-2}	4.1429×10^{-2}	9.1655×10^{-2}	1.0000×10^{-1}	2.4333×10^{-2}

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