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Battery Aging Prediction Using Input-Time-Delayed Based on an Adaptive Neuro-Fuzzy Inference System and a Group Method of Data Handling Techniques

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Abstract: In this article, two techniques that are congruous with the principle of control theory are utilized to estimate the state of health (SOH) of real-life plug-in hybrid electric vehicles (PHEVs) accurately, which is of vital importance to battery management systems. The relation between the battery terminal voltage curve properties and the battery state of health is modelled via an adaptive neuron-fuzzy inference system and a group method of data handling. The comparison of the results demonstrates the capability of the proposed techniques for accurate SOH estimation. Moreover, the estimated results are compared with the direct actual measured SOH indicators using standard tests. The results indicate that the adaptive neuron-fuzzy inference system with fifteen rules based on a SOH estimator has better performances over the other technique, with a 1.5% maximum error in comparison to the experimental data.

Keywords: state of health estimation; adaptive neuron-fuzzy inference system (ANFIS); group method of data handling (GMDH); artificial neural network (ANN); electric vehicles (EVs); capacity degradation; lithium-ion battery; time-delay input

1. Introduction:

Notwithstanding the Paris Agreement, a technological transient from a hydrocarbon-based economy to the post-petroleum era, there is less tangible projective evidence of declining fossil-fueled based economies all over the world. For instance, recent investigation into the projection period, conducted in 2017 by the U.S. Energy Information Administration [1], indicates that the demand for liquid fuels will increase from 95 to 113 million barrels per day. The proportion of the transportation demand to the petroleum demand and other liquid fuels has been predicted to increase from 54% to 56%, leading this sector to be the main topic of electrification [2]. Nevertheless, the electrification of the transportation sector with existing electrical infrastructure leads the power system to collapse. However, it can be prevented if electric vehicles are coordinated and scheduled for a proper charging time-period and rate. In addition, recent progress in harnessing renewable energy sources (RESs), and improving battery characteristics shows that it is possible to completely mitigate the impact of connecting a large fleet of electric vehicles (EVs) on the power system. The majority of scientists have reached a consensus on viable alternatives for fossil fuels, mainly wind and solar energy, which have relatively low generation costs as well as high generation potential, respectively. However, their fluctuations in output are a serious problem [3]. To alleviate the oscillations of renewable generation sources, the following four possible approaches have been proposed:

(1) Coupling renewable energy systems with different generation characteristics in wider distribution via the transmission grids;
(2) Responding to the demand by adapting consumption patterns;
(3) Employing fossil-fueled utilities as a traditional back-up (either for meeting peak demand or providing spinning reserve); and
(4) Equipping the grid with storage devices such as compressed air storage, battery storage, and hydro pump storage.

Nevertheless, these approaches suffer from different drawbacks and limitations. For instance, dealing with the uncertainties of the renewable energy sources with different characteristics that are subjected to their inherent dependency on the weather conditions is a challenging task. Concerning the second approach, adapting consumers' patterns would require a new infrastructure to control the consumers' equipment. Regarding the main drawback of the third solution, fossil-fueled utilities would increase the environmental concern, which is contradictory to the objective of the Paris Agreement. Moreover, electrical vehicles and electrical energy storage systems equipped with lithium-ion batteries assume important roles as both back-up supply systems and primary energy sources. Indeed, energy storage systems (ESS) and electrical vehicles can be used to manage the demand in response to severe times (e.g., when RESs have fluctuations and load exceeds generation). Therefore, ESSs and EVs (in vehicle-to-grid [V2G] services) have been considered as great candidates to provide regulation services for frequency fluctuation, voltage deviation, and ancillary services.

However, EVs and ESSs whose V2G capability decreases because the battery performance degrades over time, decreasing both the energy and power capabilities as a result of the dynamic nonlinear nature of the electrochemical reactions, which are impacted by external states such as charge and discharge methods, usage, temperature, and the chemical makeup of the cell. In the meanwhile, battery technology is developing rapidly and battery cells with higher energy and power densities are becoming available. Hence, improving the performance of the battery management system (BMS) is an equally important task to make the battery reliable, safe, and cost-effective [4]. Indeed, the accurate estimator algorithms are essential for the smart battery management to estimate and measure the functional states of the battery, and it should contain state-of-the-art mechanisms to protect the battery from hazardous and inefficient operating conditions. In this regard, extensive research has been carried out for lithium-ion battery systems, investigating their high power density, energy efficiency, fast charging capability, light weight, steady-state float current, wide operating temperature range, low self-discharging rate, and the possible memory effect [5].

Furthermore, both the prognostications and engineering maintenance are key figures in various industry sectors such as aerospace, chemical, automotive, and so forth. Hence, the obvious formidable obstacles to wholesale EVs is a lack of confidence in the battery life-time and performance [6], leading the authors to look into two intelligent algorithms, which are capable to be implemented in the existing BMS hardware. The state of health can be estimated and classified into offline and online procedures, which have different advantages and drawbacks in terms of accuracy, time duration, and implementation. Based on the advantages and disadvantages, vehicle manufacturers select a suitable technique according to the application. Battery capacity estimation, referring to energy capability, poses tremendous challenges to researchers, whose attempts have turned to the relationship between capacity fade and an increase in battery resistance. Nevertheless, it has been observed that the changes in battery impedance cannot be exactly related to the capacity fade. Moreover, this approach needs extensive laboratory investigations to establish the correlation function [7].

Considerable research has been recently conducted on state of health (SOH) estimation models, which can be split into the following groups: electrochemical models (EMs), equivalent circuit models (ECMs), and data-driven or black-box models [8,9]. Electrochemical models are established to replicate the growth of a solid electrode interface (SEI) in lithium-ion and describe its influence on capacity degradation. Indeed, they are built based on concentrated solution and porous electrode theories. This means that the electrochemical models describe and elaborate the basic understanding of the electrochemical reaction inside the battery [10]. The EM includes mutually coupled non-linear

partial differential equations (PDEs), increasing the numerical complexity and computational efforts, which poses difficulties in the real-time implementation phase, or large-scale simulation as a life-time prediction [11]. In this regard, desperate attempts to reduce the numerical complexity have been recently made through model-order reduction. In the literature [9], a dual SOH and state of charge (SOC) estimation technique has been proposed, by applying the sliding mode technique to the reduced version of PDE, namely a single partial model. The results showed that the proposed technique can track the SOH and SOC accurately. The advantage of the EM approaches is their independence from environmental conditions. On the other hand, as mentioned previously, the EM approaches require intensive computational efforts for system identification, because of a great quantity of parameters [12]. Moreover, the EM approaches are usually created for a particular type of battery consisting of specific anode and cathode materials [13].

The EC models are featured with ease of implementation and parameterization, as well as acceptable modeling accuracy [14]. The EC model completely depends on the environmental and operating conditions (e.g., SOH and SOC). This dependency on model parameters, derived from the operating conditions, can be addressed and captured via a look-up table, needing extensive experimental efforts to collect a sufficient dataset to describe a broad range of operating conditioning for batteries. The ECM's parameters can be estimated and updated via open-loop or close-loop methods. For the later method, an accurate EC model is required [15], and the battery parameters should be updated according to the aging state of the battery, which is a challenging task. Many techniques have been developed and some combined algorithms have been used to estimate SOC (directly or indirectly through the estimation of the open circuit voltage [OCV]), consequently estimating the SOH, such as the extended Kalman filter (EKF) and unscented Kalman filter (UKF). The EKF and UKF are effective techniques for SOH estimation. For instance, in the literature [16], a novel joint SOC and capacity estimator based on EKF has been introduced. The results showed that the proposed technique can capture the variation of the parameters in varying operating conditions and battery aging. Similarly, the authors of [17] proposed a new technique for SOH and SOC estimation, employed Coulomb counting method (CCM) to estimate SOC, taking the benefits of EKF to reduce accumulative errors of CCM, due to the current sensor noises. Moreover, the SOH was estimated based on the relationship between the dis/charge current and estimated SOC. The results demonstrated a reasonable estimation of SOH and SOC. These techniques are called joint estimation, and can estimate the SOH of the battery as accurately as the battery is modeled. This means that the accuracy is highly dependent on how the battery is modeled. Moreover, large matrix operation and inversions are required, leading to a high complexity. Furthermore, the joint estimation method may have poor numerical conditioning and suffer from instability [7]. Nonetheless, for this method, a dual estimation technique has been implemented, meaning that instead of one estimation algorithm, two adaptive filters are used. One of the filters estimates SOC and the other one is employed for the estimation of the model parameters. Sometimes, instead of the second filter used for model parameters identification, evolutionary algorithms are used [18]; a battery model was established and then a genetic algorithm was used to identify the model parameters and then estimate the SOH. In the literature [19], a multi-scale framework EKF was introduced to effectively estimate the state and parameters of the ECM, applied to a Li-ion battery for the capacity and SOC estimation. The results indicated that the proposed technique has a less than 3% error for the SOC estimation. In contrast to the joint estimation, the dual-technique consists of two adaptive filters. This technique demands a lower computational effort and the dimensions of the respective model matrices are lower than the joint estimation technique. In the literature [20], an effective joint SOH and SOC estimation technique was introduced. In this work, KF and UKF were combined to predict the state of the battery. The result regarding the SOC estimation is promising; nevertheless, the error of the SOH indicator is around 20%. In the literature [15], an adaptive sliding mode observer was employed to estimate the SOH and SOC of the Li-ion battery. The ECM consisted of two resistor and capacitor networks; furthermore, the results showed a high performance and robustness on the SOH and SOC estimations. However, similar to the joint technique, an accurate battery model is essential for the SOC and SOH estimations. Indeed, observer techniques, known as a close-loop method, whose

adaptability and effectiveness are utterly dependent on the credibility of the EC models and the robustness of the technique [10].

As stated previously, the techniques employed in ECM, suffer from inaccuracy owing to the lack of thorough understanding of the electrochemical dynamics and physics of the battery [21]. This drawback could be lessened via data-driven models, utilizing the information of the measurement ensemble. Consequently, prior knowledge of electro-chemistry is not required as a result of their capability to work with imprecise data and their self-learning ability [22]. Machine learning is categorized under data-driven method, which are widely employed for battery SOH estimation. In the literature [23], a recurrent neural network was used to monitor the SOH of a high-power lithium-ion battery. Lu et al. [24] proposed a group method of data handling, recognized as a polynomial neural network, in order to estimate the SOH of Li-ion batteries, and the results show a 5% error vs. the experimental data. The authors have concluded that the technique is universally valid for other types of battery chemistries. More recently, Chaoui et al. [5] employed an artificial neural network technique to estimate SOC and SOH directly and simultaneously. The technique used in the article is a useful tool for analyzing the system dynamics that are subjected to uncertainties [25]. In the literature [26], a naive Bayes model was introduced to predict the remaining useful life of a battery under different operating conditions. The comparative results showed the superiority of the proposed technique over the support vector machine. To reduce and avoid the need for computing power and a complex battery model, as well as considering the random driving cycle, researchers have been compelled to investigate the capacity degradation phenomena corresponding to SOH during charging or discharging processes, which could be more predictable than those methods mentioned previously [27]. Eddahech et al. [28] proposed a constant-voltage (CV) step as an indicator of capacity degradation. Then, four battery technologies were compared to show that the implemented method is very accurate by comparison with the classic discharged capacity measurements.

Motivation, Objective, and Innovation Contribution

Considering the limitations of the measurement devices in the present BMS, many external features of the battery are hard or even impossible to obtain in actual operation. Moreover, the applications of the above-mentioned methods are also limited by the computational capability of a real BMS. To address the above drawbacks of the methods described in the literature, this article proposes two states of health estimation techniques for Li-ion batteries, and then, another technique has been developed and compared to show the robustness of the proposed technique in this field. In this article, the proposed method requires only two external states (voltage and current), making the method suitable for EV applications. The key contributions of this article are summarized as follows:

- Employing an input time-delayed strategy to handle dynamic information of system.
- The Adaptive Neruo-fuzzy Inference System (ANFIS) and group method of data handling (GMDH) techniques are employed to analyze the relational grade between the SOH and selected features.
- Developing two data-driven frameworks to estimate the SOH. This article utilizes the fuzzy C-means clustering algorithm to tune and adjust the ANFIS parameter in advance, to create the initial rules.
- Accurate and effective validation of the framework in comparison to recently published articles and other methods.

The paper is organized as follows: in Section 2, a brief introduction is done regarding the group method of data handling and adaptive neuro-fuzzy inference system; in Section 3, both the discussion and comparisons between the proposed techniques are provided. The outcome of the article is summarized and concluded in Section 4.

2. Proposed Techniques

Based on the literature, modeling the relation between external and internal states is required for battery state estimation. Consequently, a battery model is needed for accurate estimation. Moreover, batteries are complicated electrochemical devices with non-linear behavior, affected by various internal and external states. This behavior can be described by a model whose formulation comprised of both uncertain and unknown parameters, but structurally known. In addition, describing the relationship between the battery terminal voltage property and battery SOH is an arduous task. As known from the literature, the charging process of an EV battery system includes two sub-processes, constant-voltage (CV) charge and constant-current (CC) charge. Charging or discharging of a certain amount of capacity (Ah) leads to a lower voltage change in fresh battery cells, while the same amount of Ah creates a higher voltage change in an aged cell for the same type of battery. This principle, the determination of the differential voltage responses to the ampere-hours discharged or charged from the battery before and after discharging or charging, is almost employed as the capacity estimation method. So, in this method, after a certain amount of energy throughput, the variation of voltage response is calculated and compared to the experimental data. This method is a practical solution for battery capacity monitoring [29–31]. The advantage of this method could reside in low inputs.

As can be seen in Figure 1, the terminal voltage curves are plotted at three different SOH levels while the batteries were charged using constant-current charging profile. The terminal voltage curves considerably vary from cycle to cycle. For instance, the terminal voltage curve of the battery at the beginning of life (BOL) has a lower slope than the voltage curves at 71% SOH. In addition, the initial, mean, and final voltages are not equal in the voltage property curves at different SOH levels. Hence, it can be concluded that the SOH can be reflected by the terminal voltage curve in a specific charging/discharging process. In other words, the battery's terminal voltage generally decreases and increases when being discharged and charged, respectively. The charging and discharging processes of a fixed number of ampere-hours lead to a lower voltage change for a battery with a higher SOH (fresh battery). On the other hand, a higher voltage change takes place when the battery's SOH is lower (aged battery). Figure 1 shows the battery charging profile based Lithium-ion battery (LIB) at different SOH from 97% to 71%, aged at 25 °C. For instance, the blue line represents 97% SOH, has a lower slope than the red line, and corresponded to 95% of the nominal capacity. In addition, the line with 71% SOH has a bigger slope than the line with 95% SOH.

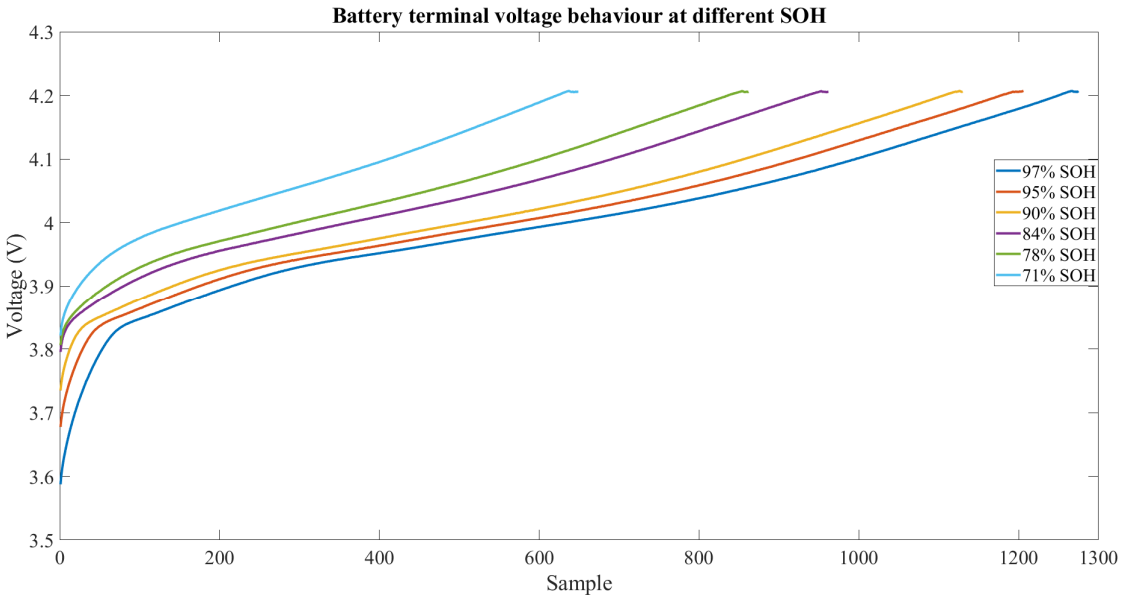

Figure 1. Terminal battery voltage at constant-current charging protocol (25 °C). SOH—state of health.

2.1. Group Method of Data Handling

The group method of data handling (GMDH) neural networks is a self-organized algorithm, meaning that the connections of the network (connections between neurons) are selected throughout the training phase to optimize the network [32]. In this approach, the neurons are completely not connected with the function nodes. Moreover, the number of layers, neurons in hidden layers, and active neurons are automatically configured, because of their self-organized capability. Furthermore, the network structure is modified until the best structure is accomplished, and thereafter, the optimized network defenses the dependency of the output values on the most notable input variables. It should be mentioned that GMDH can be employed in a wide range of fields, such as complex system modeling, forecasting, data mining, and knowledge discovery. The relation between inputs and outputs can be described as follows:

$$y = a_0 + \sum_{i=1}^{M} a_i x_i + \sum_{i=1}^{M}\sum_{j=1}^{M} a_{ij} x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{k=1}^{M} a_{ijk} x_i x_j x_k + \ldots \tag{1}$$

where $(x_1, x_2, \ldots, x_M), (a_1, a_2, \ldots, a_M)$ and M are the input variables, the coefficient, and the number of input variables, respectively. By applying input data as a matrix, N point of observations of M variables are included. In the learning step, the network is tuned and estimates the coefficients of the polynomial, as described by Equation (2), and the remaining data samples are utilized to choose the optimal structure of the model, which can be realized by minimizing the error between the expected output (real value) and the estimated value. In this regard, Equation (3), known as a mean square error, is defined as a cost function of the algorithm.

$$y = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{2}$$

$$\frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n)^2 \tag{3}$$

where $\hat{y}_n$ and y_n are the estimated and expected values, respectively, and N is the length of the training dataset. The input variables are considered as pairs of (x_i, x_j), as can be seen by Equation (2). The regression polynomial is created and then iterations continue from two to three steps, until the mean square error of the test data converge to a constant value. The configuration of the group method of data handling is depicted in Figure 2.

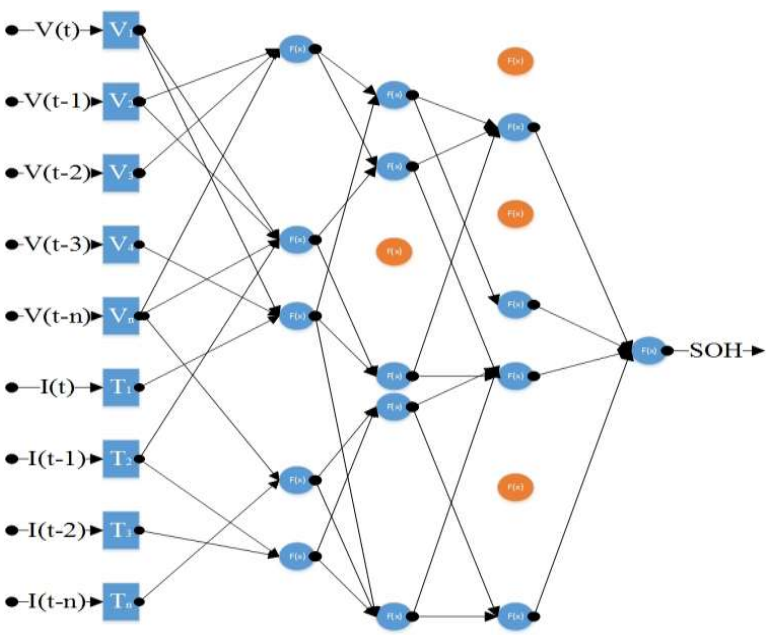

Figure 2. Group method of data handling (GMDH) structure.

Figure 2 illustrates the optimized structure, configured automatically by minimizing the cost function, as defined previously. Furthermore, some node functions were not connected to the network, as can be distinguished in Figure 2.

2.2. Adaptive Neuro-Fuzzy Inference system

Fuzzy logic (FL) is a robust system that transforms variables to mathematical language, which is consistent with the ability of human knowledge modeling. While, fuzzy logic tries to model either linear or non-linear systems, it is not possible to be trained by itself in a stochastic condition. Therefore, fuzzy logic systems are dependent on their operation rules, which should be defined by the experts who conclude, using their intuition, the parameters associated with membership functions. To overcome this problem, FL can be combined with artificial neural networks (ANNs), which have a remarkable ability to learn from imprecise data. Hence, combination of ANNs and FL procedures lead a better parameterization, which presents the fuzzy logic inference, known as the adaptive neuro-fuzzy inference system (ANFIS). Indeed, fuzzy logic and ANNs have both substantial benefits and drawbacks, which should be taken into consideration in terms of system modeling. In fuzzy logic language, called 'fuzzily', if–else statements are used to model the system by human knowledge. Although FLs are not capable of capturing measurement values, and use them to either adjust or modify the parameters like the Gaussian membership function variables, ANNs have the capability to be tuned and learnt by experimental data, leading a mathematical model not to be included in the system modeling, which can be possible by input–output mapping. Moreover, it has been demonstrated that the ANFIS is one of the techniques that can be utilized to any type of battery with various operating conditions (e.g., partial discharging, constant charge, and discharge processes) [33].

Two common fuzzy style inferences are Mamdani-style and Sugeno-style, which have been presented by Lotfi Zadeh and Takagi-Sugeno-kang, respectively [3]. To provide a better understanding, an ANFIS structure with two-input one-output is illustrated in Figure 3. The rule base considers two fuzzy 'if–then' rules of Takagi and Sugeno's type, which are as follows:

$$rule\ 1:\ If\ \ x \to A_1\ \ and\ \ y \to B_1,\ then\ Z_1 = p_1 x + q_1 y + r_1$$

$$rule\ 2:\ If\ \ x \to A_2\ \ and\ \ y \to B_2, then\ Z_2 = p_2 x + q_2 y + r_2$$

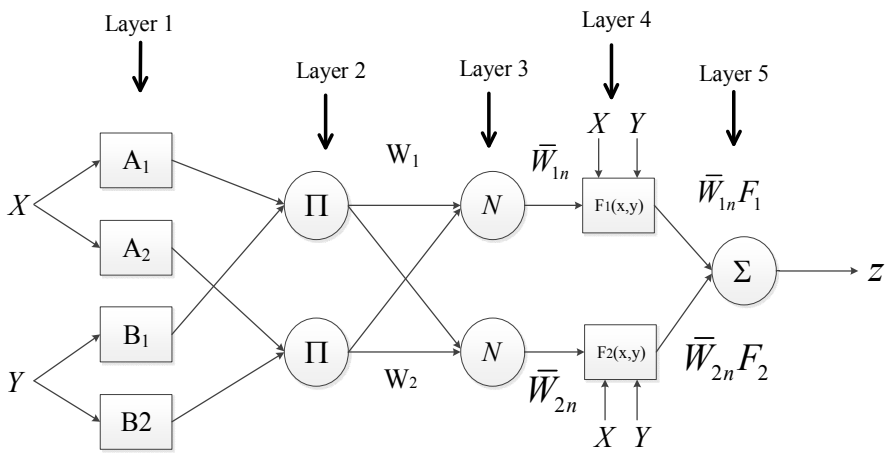

Figure 3. A general adaptive neural-fuzzy inference system [2].

The basic structure of ANFIS, considering as a fuzzy inference system, is a five-layered feedforward type, ANN, including different purpose-built types of nodes (e.g., non-weighted, adaptive, and non-adaptive connection links). The different layers can be classified into five-layers, which are as follows:

Layer 1: This layer is known as fuzzy-fication layer, which fuzzifies the input variables; every *i* node consists of a node function, which is $O_{1,i} = \mu_{Ai}(x)$, symbolized by A_i, x, O_{1i}, where A_i is the linguistic label according to the node function, x is the input to the node, and $O_{1,i}$ is the membership function of that, specifying the level for the assumed *x*. Hence, the membership function ascertains the membership level from the given input values. For a bell-shaped function, three parameters for each node should be defined, for which the maximum and minimum possible value are 1 and 0, respectively; where its generalized function can be mathematically described as follows:

$$\mu_{A_i}(x) = \frac{1}{1+[((x-c_i)/(a_i))^2]^{b_i}} \tag{4}$$

where $\{a_i, b_i, c_i\}$ are the set parameters, called as premise parameters, μ is commonly chosen as bell-shaped or gauss-shaped, x is the first input variable, and the membership function variables are adjusted by changing the aforementioned parameters whenever the first input variable is fed to the ANFIS.

Layer 2: Is called 'fuzzy and', because in this layer, only 'AND' operators are allowed. This layer is utilized to compute the firing robustness of every rule. It means product operation (see Equation [5]) referred to the weighting factor of the corresponding rule, is used.

$$O_{2,i} = w_i = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2) \;\; for \;\; i = 1,2 \tag{5}$$

Layer 3: Is known as 'normalization' term. The firing strength of each rule is normalized via computing the ration of each rule's firing strength to the total of each rules. In Equation (6), $\overline{w_i}$ is defined as the firing strength of each rule, as illustrated below:

$$O_{3,i} = \overline{w}_i f_i = \frac{w_i}{\sum w_i} = \frac{w_i}{w_1 + w_2}, \;\; for \;\; i = 1,2 \tag{6}$$

Layer 4: Is recognized as 'defuzzification'. This layer tries to compute the output of the previous layer, based on its node function; each node function is adaptive in accordance with the node function, as given by Equation (7).

$$O_{4,i} = \overline{w}_i \times f_i = \overline{w}_i (p_i x_i + q_i x_i + r_i), \;\; for \;\; i = 1,2 \tag{7}$$

where $\overline{w}_i$ is the output of the third layer and the parameters (p_i, q_i, r_i) are set parameters, which are being assumed by the conditions of the determined parameter. The parameters in the fuzzy inference layer are considered as consequent parameters.

Layer 5: Is called 'aggregation'. This layer is utilized to compute the total of the outputs of all of the rules to produce the overall ANFIS output, whose equation is represented as follows:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} = f_{out} \tag{8}$$

The aforementioned architecture is employed to adjust ANFIS model for SOH estimation, as discussed in the next section.

3. Result and Discussion

Many methods have been proposed in the literature to estimate SOH, whereby accurate battery parameters are needed to build the empirical model, which could be inefficient and expensive.

Nevertheless, the above developed techniques are capable of dealing with the complexity of the system modeling, insufficient data, and can still describe the system behavior.

3.1. Experimental Data

In this work, the experimental data from Prognostics Center of Excellence at National Aeronautics and Space Administration (NASA) Ames is employed to train and validate the proposed approaches [34]. This approach leads the comparison of the proposed techniques with that of recently published papers using the same dataset to be easier. The dataset consists of four batteries, aged through three different operational profiles conducting alternately in the dataset, namely impedance, charge, and discharge profiles. The impedance measurement process was performed by employing the electrochemical impedance spectroscopy (EIS) technique. Moreover, in the regular charge and discharge cycle, the batteries were charged and discharged at CC of 1.5 A and 2 A, respectively. In the charge step, 1.5 A is imposed to the batteries to reach the maximum voltage of 4.2 V, followed by the CV process, until the current decreased from 1.5 A to 20 mA. Nevertheless, in the discharge profile, the CC discharge step was conducted by reaching the voltage of 2.7 V, 2.5 V, 2.2 V, and 2.5 V for batteries, No. 05, 06, 07, and 18, respectively. As a consequence of reoccurring the above procedure, the capacity of the batteries reached 70% of the nominal capacity.

3.2. Short-Term State of Health Estimation

In this subsection, the performance of the short-term SOH estimation is presented by employing the proposed techniques. Both the GMDH and ANFIS are trained by the collected dataset. The inputs and the outputs of the system in the training phase are the battery terminal voltage and the SOH, respectively. The beginning-of-life (BoL), corresponding to a fresh battery, is defined as a 100% SOH, and the 167th cycle, when the capacity has reached the 1.4 Ah, is considered as the end-of-life. Moreover, the algorithm uses the unit-time-delays to consider the battery voltage at past time frames. The voltage is normalized, which is a standard procedure when such intelligent techniques are used. Thereafter, the normalized dataset after the computing and estimating procedures will be de-normalized. Owing to the capability of improvement in the read performance of the database, this technique is used. Indeed, each sample is divided by the maximum possible measurement. For instance, a measurement of 4.2 V constitutes as number 1, while 0 V is represented as number 0, and every other value is between 1 and 0. Furthermore, it should be noted that EVs are not always charged at a certain state of charge, which means that the technique should be able to estimate the SOH at different SOC levels, corresponding to different initial voltages. The proposed techniques, GMDH and ANFIS, were trained by the experimental results of battery No. 05. As mentioned previously, during the training phase, the structure and weights of GMDH and weights of ANFIS could be optimized and adjusted in terms of minimizing the error between the estimated SOH from the network, and the training targets from the experimental data. Then, the techniques are validated by employing the experimental data from battery No. 06. For the GMDH whose parameters are the maximum number of neurons in a layer, the maximum number of layers and selection pressure are set to 10, 5, and 0.6, respectively. It should be pointed out that the dataset for the training phase includes all of the voltage samples corresponding to 0% SOC to 100% SOC.

The GMDH parameters, maximum number of neurons in a layer, maximum number of layers, and selection pressure are set to 250, 10, and 0.6, respectively. For validation, battery No. 06 was used, whose experimental results were used to test the estimation accuracy of the GMDH technique. The actual and estimated SOH are depicted in Figure 4. The blue line shows the actual SOH and the red line indicates the estimated SOH at first and second cycles with 0.052 mean square error, and 0.23 root mean square error. It is observed that the relationship between the battery voltage and estimated SOH closely matches the actual test dataset. Moreover, the RMSE and MSE show that the GMDH has successfully discovered the effects of aging of the battery voltage behavior.

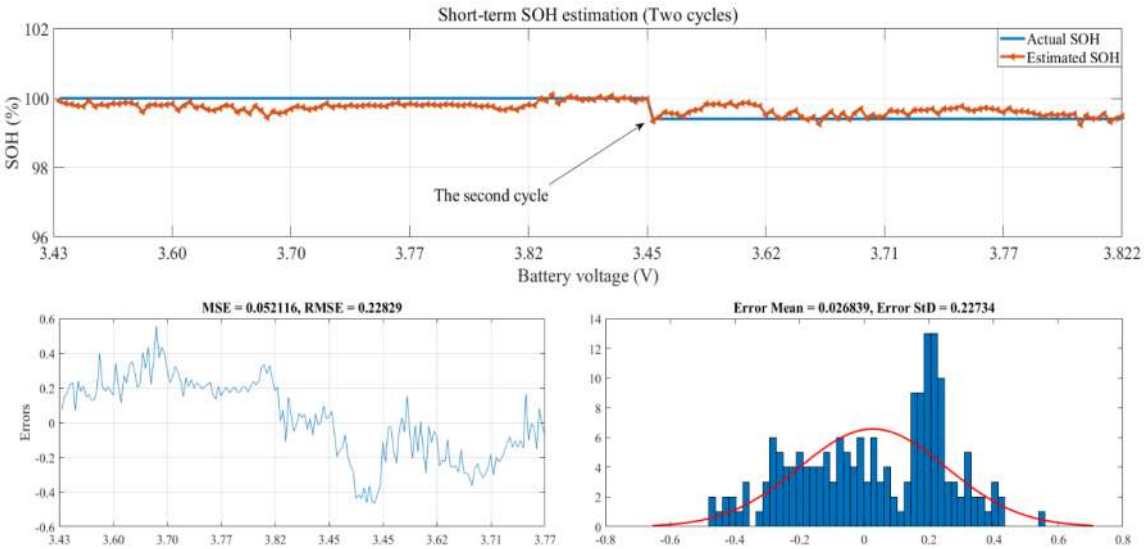

Figure 4. Experimental and estimated results of state of health (SOH) vs. battery voltage by employing GMDH (No. 06) for two cycles.

With regard to the second technique, as mentioned earlier, the combination of fuzzy logic and NNs leads to the ANFIS structure, which is classified under adaptive networks. Consequently, ANFIS has the ability to reach a conclusion from unclear and complex data, because of the fuzzy logic, with the capability to work from imprecise data [35]. In this regard, this technique is utilized to estimate the SOH from a set of curves whose shapes depend on the state of the system. Furthermore, the ANFIS cannot work without a training phase. Therefore, the battery terminal voltage during constant current charge profile at different SOH is prepared. Then, the membership functions should be adapted to the battery charge curves, which are diverse at different SOH levels. It should be pointed out that the constant-voltage sub-process is not included in the input dataset. The number of initial ANFIS rules for the first input was set to 15, these rules were generated using the fuzzy C-means (FCM) clustering method, and then the ANFIS was trained and tuned by the experimental results of battery No. 05. Moreover, the method used for optimization of the parameter of ANFIS, is a combination of back-propagation and least-square estimation. Note that the trained dataset consists of all of the voltage intervals, starting from 0% to 100% SOC. The dataset, related to the battery No. 06, is utilized to test the developed algorithm.

The errors between the experimental data (actual SOH) against the estimated SOH at different voltage levels are illustrated in Figure 5. The mean squared error (MSE) and root mean squared error (RMSE) are 0.009 and 0.094, respectively. As can be inferred from the results, the ANFIS has better performance compared with the GMDH. The results, shown in Figure 4, have a maximum error below 0.3. Moreover, the overestimation and underestimation is lower than that of the previous technique, which demonstrated the adaptive capability of the ANFIS technique.

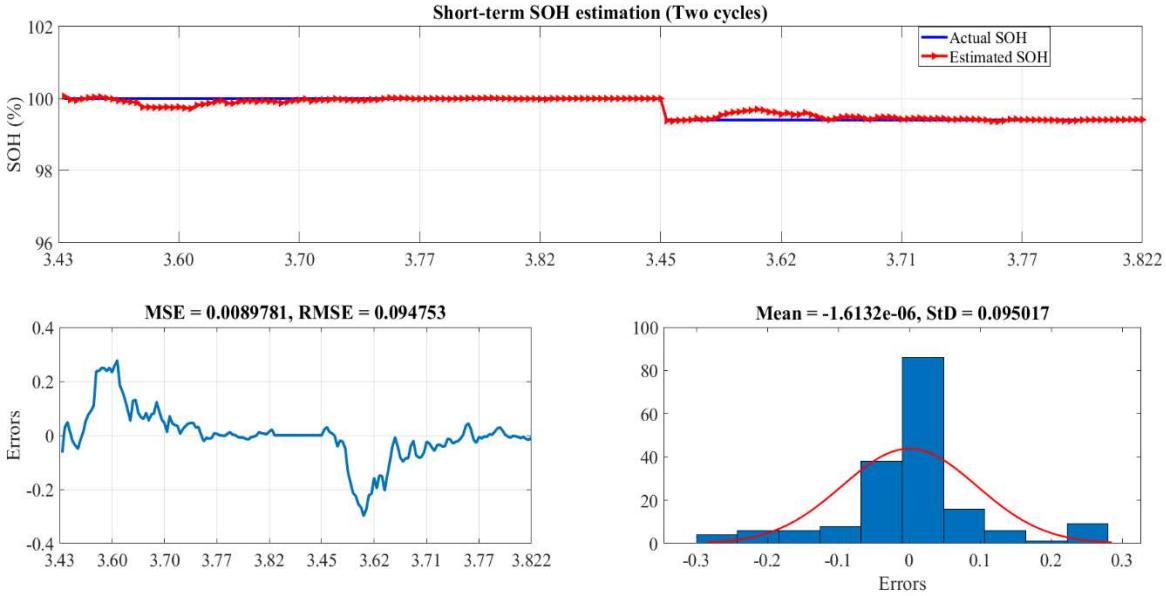

Figure 5. Experimental and estimated results of SOH vs. battery voltage by employing ANFIS (No.06) for two cycles.

3.3. Long-Term State of Health Estimation

In this subsection, the proposed techniques for the long-term battery state of health estimation are also evaluated. Note that in this procedure, all of the short-term SOH and voltage cycles are integrated to build one macro time scale concept. The charge data for 87 cycles of battery, No. 06, are employed to evaluate the proposed techniques for long-term estimation capability.

Figure 6 shows the long-term SOH estimation of battery No. 06. The obtained MSE and RMSE for the SOH estimation are 0.714, and 0.845, respectively. It can be seen that the GMDH, trained and tuned by battery No. 05, can be used to estimate the SOH for other batteries. Nevertheless, it is observed that, despite the better performance of GMDH for short-term estimation, in long-term SOH estimation, the fluctuation of GMDH is the most noticeable. According to Figure 6, the GMDH could not estimate the 1st, 21st, 54th, and 74th accurately. It can be concluded that the GMDH technique for long-term SOH estimation is instable.

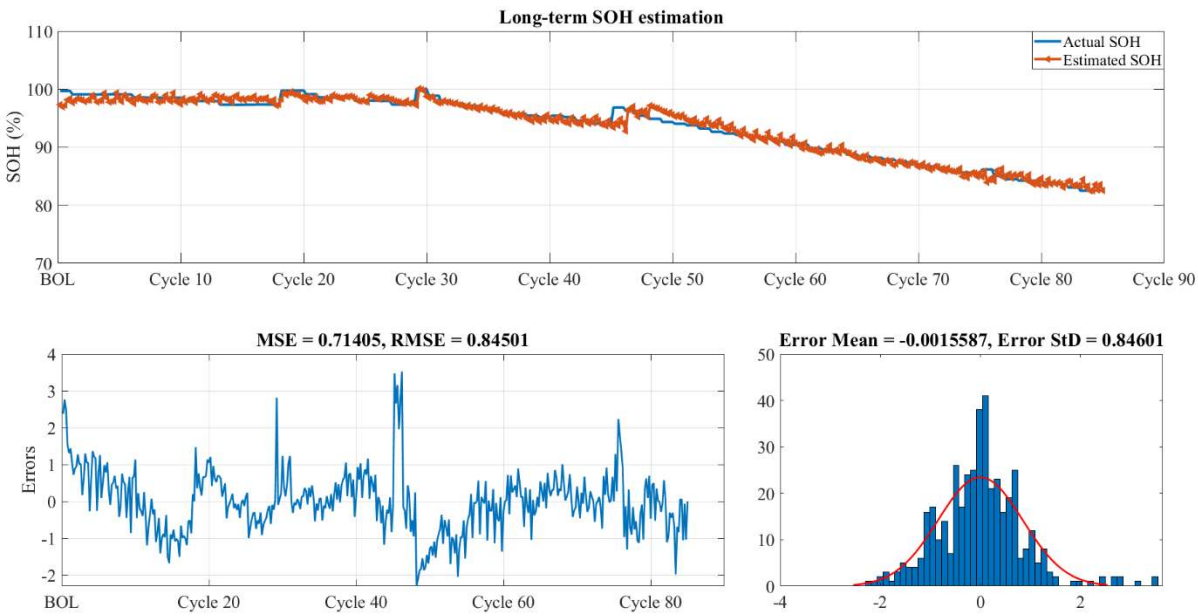

Figure 6. Long-term SOH estimation via GMDH for the 87 discharge cycles of battery No. 06.

The results of SOH estimation for battery No. 06 based on ANFIS, are plotted in Figure 7. As it is noted in the figure, the MSE and RMSE are 0.041 and 0.203, respectively, which shows a better stability from the GMDH for the long-term SOH estimation. It can be observed that the ANFIS has successfully learned the effect of capacity degradation on the battery terminal voltage. Therefore, overcharging and deep-discharging can be avoided, and also, the proposed techniques can be used for smart battery charging management, as ANFIS and GMDH have the capability to respond to an optimization algorithm as soon as they receive the inputs of the system.

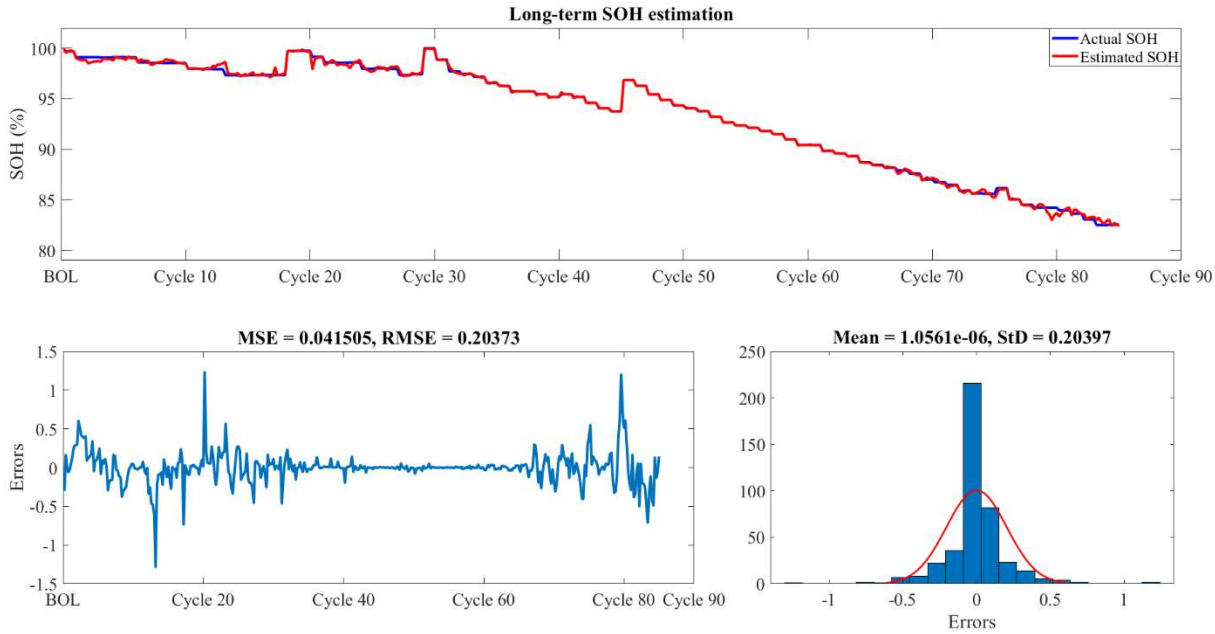

Figure 7. Long-term SOH estimation via ANFIS for the 87 discharge cycles of battery No. 06.

Table 1 presents the performance of the evaluation, comparing the proposed techniques with the recent published articles. As shown in the table, the ANFIS model obtains a much better performance over the GMDH model. For instance, the RMSE and MSE on battery No. 06 based on GMDH is 0.845 and 0.714, while the RMSE and MSE based on ANFIS is 0.203 and 0.041, respectively. Moreover, in terms of comparison, the present results and the resent published articles used same dataset from NASA, the performance of the models introduced in the literature [16,24,36] are compared in Table 1. As can be observed, the RMSE and MSE based on the ANFIS model are much better than the introduced models. Nevertheless, the following limitations need to be addressed in future studies:

1. While machine learning demonstrated an acceptable self-adaptation and high non-linearity modeling capability, a large amount of experimental data is required to obtain a high accuracy.
2. Although the introduced SOH method is more predictable and accurate under charging and discharging processes, it is not a usable method for plug-in hybrid electric vehicles (PHEVs)/PEVs when they are connected to smart charging infrastructure.

Table 1. Root mean square error (RMSE) results of long-term capacity estimations of adaptive neruo-fuzzy inference system (ANFIS), group method of data handling (GMDH), and a recent published article. MSE—mean square error; QGPER—quadratic polynomial mean function; DGA—geometry based approach.

Error	Ref. [36] QGPFR	Ref. [16] GPR-SE	Ref. [24] GMDH-DGA	Present Study ANFIS	Present Study GMDH
RMSE (battery No. 06)	5.12	1.7064	-	0.203	0.845

MSE (battery No. 06)	-	-	0.360	0.041	0.714

4. Conclusions

In this article, two data-driven techniques are developed for the state of health estimation. The developed techniques utilize an adaptive neuro-fuzzy inference system and group method of data handling to train the relation of the battery terminal voltage and state of health, enjoying the advantage over existing methods, as mentioned previously (e.g., lower inputs, described system behavior), with no need for computing power and a complex battery model. The comparative merit of the method and techniques implemented in this paper, compared to the existing ones in the literature, can be concluded in two main points. Firstly, the techniques are not dependent on any specific battery model, due to the fact that they are data-driven techniques, as can be inferred. The employed techniques can be applied to a great variety of battery technologies. Secondly, the battery operating dataset is applied to these techniques to analyze the internal structure, which is inaccessible. The comparison between the experimental and estimated results showed a robustness of the developed techniques, fast convergence performance, and outstanding accuracy for the battery health estimation.

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Abbreviations

ANN	artificial neural network
ANFIS	adaptive neruo-fuzzy inference system
BMS	battery management system
CC	constant current
CV	constant voltage
DG	distributed generation
DGA	geometry based approach
ESS	energy storage system
EV	electric vehicle
EKF	extended Kalman filter
G2V	grid-to-vehicle
GHG	greenhouse gas
GMDH	group method of data handling
GP	Gaussian process
HRES	hybrid renewable energy system
ITDNN	input time-delayed neural network
KF	Kalman filter
LS	least squares
NN	neural network
NEDC	new European driving cycle
MSE	mean squared error
PS	power system
PF	particle filter
QGPFR	quadratic polynomial mean function (GP)
RMSE	root mean square error
RBC	remaining battery capacity
SG	smart grid
SOC	state of charge
SOH	state of health

V2G	vehicle-to-grid
NPF	nonlinear predictive filter
MSE	mean square error
OCV	open circuit voltage
PHEV	plug-in hybrid electric vehicle

Nomenclature

$\hat{y}_n$	estimated values
y_n	expected values
M	number of input variables
x_i, x_j	pairs of input variables
$O_{1,i}$	membership function
A_i	linguistic label
(x_1, x_M)	Input variables
(a_1, a_M)	model coefficient

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