Σχολή Ηλεκτρολόγων Μηχανικών
& Μηχανικών Υπολογιστών

School of Electrical
& Computer Engineering

Εφαρμογή Μεθόδων Νεύρο-Ασαφούς Λογικής για την Βέλτιστη Διαχείριση Φόρτισης-Εκφόρτισης Συσσωρευτών Λιθίου

Application of Neuro-Fuzzy Methods for the Optimal Management of the Charging and Discharging of Lithium-Ion Batteries

Diploma Thesis in Energy Systems
At the School of Electrical and Computer Engineer
Of Technical University of Crete

Roditis Ioannis

Supervisor: Professor Stavrakakis Georgios
Examiner: Associate Professor Koutroulis Eftychios,
Doctor Sergaki Eleftheria

Chania, Crete, August 2020

ACKNOWLEDGEMENTS

First and foremost, I would like to express my sincere gratitude to my supervisor, Professor Stavrakakis Georgios, for his guidance, invaluable encouragement and unwavering support during my thesis. I am also thankful to Associate Professor Koutroulis Eftychios for his insightful and constructive inputs and help to improve the quality of my work. I greatly appreciate the helpful advice and technical support from Doctor Sergaki Eleftheria, EDIP (Laboratory Teaching Staff).

Last but not least, I am highly obliged for the unconditional love and support given by my beloved family and friends. Without the countless encouragement and trust from them in the past several years, I would not be able to achieve this.

Roditis Ioannis
Chania, August 2020

ABSTRACT

Over the last decade, energy storage has continued to evolve and adapt to energy requirements. The battery is a widely used electrical energy storage system. To achieve an efficient battery storage system an online and correct estimation of the state of charge is essential. Furthermore, state-of-the-art batteries can be characterized as a complex technological system. In order to model and/or simulate such systems, neural networks, fuzzy logic and Adaptive Neuro Fuzzy Inference Systems are often utilized.

In this thesis, firstly, three systems (charging, discharging and hybrid electric vehicle operation) using batteries are introduced. Battery system data were produced through simulations for the training and evaluation of the proposed algorithm, based on a modified neuro fuzzy logic system. By using this algorithm the state of charge can be predicted for the three different operations of the lithium-ion battery (charging, discharging and hybrid electric vehicle operation). Specifically, in this work an Adaptive Neuro Fuzzy Inference System is implemented in order to predict the state of charge of the lithium battery. Consequently, the estimated state of charge is compared with the state of charge from the experimental data for validation (charging, discharging and hybrid electric vehicle operation). All the simulated systems and the adaptive neuro fuzzy inference system were implemented in Matlab/Simulink.

The simulation results when compared to relevant studies validated the model developed in this project, as they achieve better performance in satisfactory time. For a variety of different input data sets, the prediction error (root mean square error) for the battery state of charge ranged from 0.061 to 0.064 for charging system, from 0.275 to 0.061 for discharging and from 2.81 to 2.85 for hybrid electric vehicle. In addition, the proposed algorithm has an average runtime of some milliseconds (2msec) for the charging and discharging systems and a few seconds (50sec) for hybrid electric vehicle operation.

ΠΕΡΙΛΗΨΗ

Κατά την διάρκεια της τελευταίας δεκαετίας, η αποθήκευση ενέργειας συνεχίζει να αναπτύσσεται και να προσαρμόζεται στις ενεργειακές απαιτήσεις. Μια ηλεκτρική μορφή αποθήκευσης ενέργειας που χρησιμοποιείται ευρέως είναι η μπαταρία. Για να επιτευχθεί αποτελεσματική αποθήκευση ενέργειας σε μια μπαταρία η διαρκείς (online) και ορθή εκτίμηση της κατάστασης φόρτισής της είναι απαραίτητη. Επιπρόσθετα, οι τελευταίας τεχνολογίας μπαταρίες χαρακτηρίζονται ως πολύπλοκα τεχνολογικά σύστημα. Για να μοντελοποιηθεί-προσομοιωθεί ένα τέτοιο σύστημα εφαρμόζονται αλγόριθμοι νευρωνικών δικτύων, ασαφούς και νευροασαφούς λογικής.

Στη συγκεκριμένη διπλωματική εργασία, αρχικά, αναπτύσσονται τρεις εφαρμογές, στις οποίες γίνεται χρήση της μπαταρίας (λειτουργία φόρτισης, εκφόρτισης και λειτουργία υβριδικού ηλεκτρικού οχήματος). Από την προσομοίωσή τους παρήχθησαν τα απαραίτητα πειραματικά δεδομένα για την εκπαίδευση (training) και την αξιολόγηση (evaluation) του προτεινόμενου αλγορίθμου, ο οποίος βασίζεται σε ένα προσαρμοζόμενο σύστημα νευροασαφούς λογικής. Με την χρησιμοποίηση του συγκεκριμένου αλγορίθμου, η κατάσταση φόρτισης-εκφόρτισης μιας μπαταρίας ιόντων λιθίου μπορεί να προβλεφθεί για τις τρεις διαφορετικές λειτουργίες της (λειτουργία φόρτισης, εκφόρτισης και λειτουργία υβριδικού ηλεκτρικού οχήματος). Συγκεκριμένα, επιτυγχάνεται εκτίμηση της κατάστασης φόρτισης μιας μπαταρίας λιθίου με την προτεινόμενη τεχνική νευροασαφούς λογικής, όπου συγκρίνεται η κατάσταση φόρτισης που προκύπτει από την τεχνική με την κατάσταση φόρτισης, που έχει ληφθεί από τα πειραματικά δεδομένα για κάθε σύστημα ξεχωριστά (λειτουργία φόρτισης, εκφόρτισης και λειτουργία υβριδικού ηλεκτρικού οχήματος). Η προσομοίωση όλων των συστημάτων, καθώς και ο αλγόριθμος προσαρμοζόμενης νευροασαφούς λογικής αναπτύχθηκαν στο Matlab/Simulink.

Τα αποτελέσματα των προσομοιώσεων επιβεβαιώνουν την προτεινόμενη μεθοδολογία, όταν συγκρίνονται με αντίστοιχες μελέτες της βιβλιογραφίας, διότι επιτυγχάνει καλύτερη απόδοση σε ικανοποιητικό χρόνο. Για διαφορετικές ομάδες δεδομένων εισόδου, το λάθος πρόβλεψης (root mean square error) της κατάστασης φόρτισης της μπαταρίας κυμαίνονταν από 0.061 έως 0.064, από 0.275 έως 0.061 για την λειτουργία συστήματος εκφόρτισης και από 2.81 έως 2.85 για την λειτουργία υβριδικού ηλεκτρικού οχήματος. Επίσης, ο χρόνος εκτέλεσης του προτεινόμενου αλγορίθμου είναι της τάξης μονοψήφιου αριθμού milliseconds (2msec) για την λειτουργία φόρτισης και εκφόρτισης και κάποια δευτερόλεπτα (50sec) για την λειτουργία υβριδικού ηλεκτρικού οχήματος.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Energy storage systems provide a wide array of technological approaches to managing a power supply in order to create a more reliable energy infrastructure and bring cost effectiveness to both producers and consumers. An energy storage system is categorized by several criteria including mechanical, electrochemical, chemical and electrical techniques to store the excess electrical energy produced by all resources. Optimal scheduling of energy storage systems requires two pieces of information to be known. First is an accurate prediction of the load profile over a period of time where the energy storage unit will operate and the second aspect is the available energy in the system at the time of scheduling, which is determined through state of charge (SOC) estimation.

The battery is one of the oldest systems to store energy and was discovered by Alessandro Volta in 1800. This technology has been rapidly developed until nowadays. Over the years there have been a variety of mathematical and chemical techniques designed to facilitate the modeling task of batteries. These range greatly in complexity from very simple models capable of operating small systems like remote controls, torch lights to more complex ones such as smart grids. Soft Computing methods that have been developed from emulating intelligent phenomenon in human and nature provide a suitable framework to deal with such complications. Soft Computing involves methodologies such as neural networks (NN) and fuzzy logic (FL) and is focused on the study of adaptive mechanism to assist intelligent behavior in inconsistent and imprecise environments such as the behaviour of a battery in different load demands and power storage.

Neuro Fuzzy (NF) hybrid modeling approaches are a set of methods created by combining NN and FL. The desired qualities of both the fuzzy logic and the neural network methods support such a hybrid approach by hence generating adaptable models. These models could be linguistically represented and interpreted by fuzzy rules structure while learning from experimental data. In dynamic system identification, neurofuzzy systems incorporating a Takagi-Sugeno (TS) scheme possess a very good interpretation. However, TS based fuzzy systems may require a huge number of rules and associated coefficients in order to achieve the desired accuracy. An undesirably high computational cost is usually associated with a large network structure. The Adaptive Neuro Fuzzy Inference System (ANFIS) architecture is a classic representative of TS -based models.

In order to achieve an accurate model for SOC estimation, apart from ANFIS, we consider lithium ion batteries. A lithium battery does not require a lot of maintenance during its lifecycle, which is a big advantage since no scheduled cycling is needed, and there is no memory effect in the battery. In addition to that, the lithium battery is appropriate for hybrid electric vehicles because it has the least self-discharge rate, high energy density and high operating voltage levels. Lithium-ion batteries are commonly used in energy storage applications, such as railway transportation systems, renewable energy systems, and smart grids. They are preferred over lead-acid, nickel-metal hydride (NiMH), and nick-cadmium (NiCd) batteries due to their superior performance in energy density, voltage plateau, efficiency, lifetime, power density and aging.

All in all, this thesis investigates the ability of advanced ANFIS in charging and discharging of a lithium-ion (li-ion) Battery in three different operations (battery charging, discharging and hybrid electric vehicle operation). The system is trained and tested according to an original data set prepared for this project. The software provides aforementioned tools-system is Matlab and Simulink R2020.

1.2 Previous Work

In most systems that use a battery, a parameter that describes how much energy the battery has or how long the battery can last, is state of charge. There are many different techniques of battery SOC estimation, which are summarized in paper [1], and each of them has its most suitable field due to complex nonlinear behavior of battery. The Coulomb counting method relies on the integration of battery current with respect to time to account for the charge added or withdrawn from the battery [2][3]. Electrochemical impedance spectroscopy can be employed to assess the battery SOC in case the impedance is correlated with the energy in the battery [4]. Nevertheless, lack of accuracy is a common feature of these techniques for different reasons not limited to the clear dependency on measurements or estimations of other variables.

More mathematically exhaustive methods for direct SOC estimation depend on several variations of Kalman filter. Kalman filtering estimates the averaged SOC of the battery pack, just as what the traditional estimators do [5]. A robust extended Kalman filter is used to estimate the SOC [6]. Implement a square root unscented Kalman filter based method to estimate pack average SOC and simplified Kalman filter based method for SOC determination [7]. The large computational burden is usually an obstacle for feasible implementation of such methods.

Various versions of adaptive neuro-fuzzy inference systems (1st order Takagi-Sugeno) have been implemented in the literature in the context of battery SOC estimation. Adaptive controllers for serially connected Lithium-ion Batteries [8], ANFIS controller for SOC monitoring [9] are just application of ANFIS. In addition, with ANFIS can be implemented a fault tolerance controller [10], model identification [11] and equalization of SOC [12].

Enough training data have to be provided for black-box computing intelligence approaches. The existing fact that to predict SOC under a certain operation condition requires the training data under the same condition limits the application extension [13][14]. Occasionally the experimental data are not easy to train. So different techniques [15] and algorithms deal with this problem, for example particle swarm optimization [16]. Sometimes the qualified training data is hard to be obtained either from a lab experiment [17] or a simulation program, such as Matlab-Simulink [18][19].

CHAPTER 2: STATE OF ART

2.1 ANFIS

2.1.1 Introduction

Soft computing includes FL, NN, probabilistic reasoning, and genetic algorithms .Today, techniques, or a combination of techniques, from these areas are used to design intelligent systems. NNs provide algorithms for learning, classification and optimization, whereas FL models deal with issues such as forming impressions and reasoning on a semantic or linguistic level. Probabilistic reasoning deals with uncertainty. Although there are considerable areas of overlap between NNs, FL and probabilistic reasoning, in general they are complementary rather than competitive. Recently an intelligent system has been introduced, called neuro fuzzy system. In this chapter, the methodology of a neuro fuzzy technique, namely an Artificial Neuro Fuzzy Inference System, which has been used in this study, will be presented. In order to understand the structure of ANFIS, it is necessary to understand the basic ideas in the design of NNs and FL techniques. These will be introduced briefly in the following section.

2.1.2 Neural Network

2.1.2.1 Introduction and Historical Background

A Neural Network is an interconnected group of nodes, which has similarities to a network of neurons in the brain. A NN information processing system of is inspired by the functioning model behavior of biological nervous systems, such as the brain. A key aspect of a neural network is that it has to be trained. The neural network by virtue does not have the appropriate knowledge to solve a problem. A NN much akin to the human nervous system learns by example. In biological systems, learning involves adjustments to the synaptic connections that exist between the neurons. This is true for a neural network as well.

NN simulations appear to be recently developed. However, this field was established before the appearance of computers, and has survived several eras. The first successful simulation model, based on the working model of biological neurons, was implemented by McCulloch and Pitts. These models were based on how simple neurons worked and how they were similar to simple logic elements with thresholds. After that, a period of frustration and disrepute followed, in which Minsky and Papert highlighted the limitations of single layer perceptrons compared to multilayer systems. In other words, a perceptron could only solve linearly separable functions but not XOR or XNOR logic. Since then this field has been developed and has introduced significant commercial applications for industry.

2.1.2.2 Structure

A neural network is composed of a large number of highly interconnected processing elements (neurons) working together to solve specific problems. A single neuron can be modeled by:

$$net = \sum_{i=1}^{n} W_i x_i + W_{n+1}$$

Fig.2.1: Illustrating a single neuron

It is diagrammatically represented as:

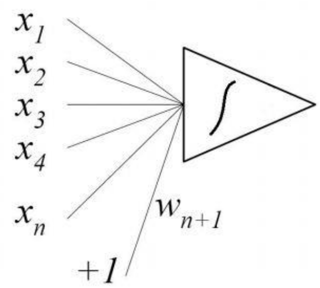


Fig.2.2: A neuron with n inputs, weights and threshold value

NNs consist of an input layer, one or more hidden layers and an output layer. Layers are interconnected to each other.

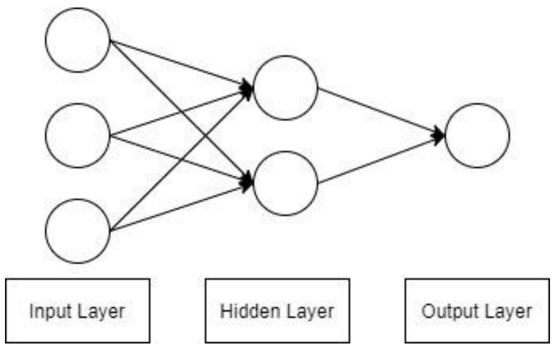


Fig.2.3: Typical Structure of a neural network

The function of an input layer is to receive input from the outside world. The function of the output layer is to provide the results of the NN predictions. The hidden layer links the input layer to the output layer. The role of the hidden layer is to extract and remember useful features and sub-features from the input patterns. In this manner, the outcome of the network can form a prediction [40].

A process known as back-propagation accomplishes the adjustment of the weights so as to minimize the error between the predicted and the target value. In order to train a neural network to perform a task, the weights of each unit must be adjusted in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights. In other words, it must calculate how the error changes when weight is changed even slightly. The back propagation algorithm is the most widely used method for determining the error derivative of weights. The basic steps involved in the algorithm are:

1. Random weights are asserted to the network.
2. An input is applied to the network and the results for all nodes are obtained.
3. By comparing the desired and obtained result the errors for each node are calculated, starting from the last node and propagating the error backward.
4. Based on the error calculated, the weights of each node are updated.
5. Steps 1 through 4 are repeated until the desired output is achieved.

2.1.2.3 Advantages and Limitations

A NN can be assumed to be an “expert” in the category of information that it has been trained. The neural network has the ability to interpret meaningful information, patterns and trends from imprecise data, which are too complex to be interpreted by other computing techniques. The following are some important features of artificial neural networks.

- Parallel Processing: The parallel processing of neural networks allows solving problems where multiple constraints come across, which is very similar to the real biological nervous system.
- Self-Organization: A NN has the ability to self-organize while learning. This helps in the visualization of low dimensional view of high dimensional data.
- Graceful Degradation: An important feature of neural network is that partial removal of components only causes corresponding degradation in the accuracy of output rather than the failure of the system.
- Continuous Adaptivity: The NN has the capability to learn from the samples (input vectors).

Neural networks are the not the perfect solution for every problem. They can only be considered to have the advantage only in the category of trained and tasked information. NN are limited by problems like the following:

- Accuracy: Neural networks are not a hundred percent accurate system. The accuracy depends on the amount of training data and the network size. Systems which have high accuracy requirements should not depend on NNs.
- Black Box: A neural network system can be represented as a black box, like the nervous system. The system learns based on training and experience but cannot justify the decision.
- Training: The amount of training data and time needed by a NN is an obstacle. Nowadays, this problem has been overcome with the vast amount of data available in the digital world.

2.1.3 Fuzzy Logic

2.1.3.1 Introduction and Historical Background

Fuzzy logic and fuzzy set theory are used to describe human thinking and reasoning in a mathematical framework. FL calculates intermediate values between absolute true and false with resulting values ranging between 0 and 1. With fuzzy logic, the degree to which an item is a member of a category can be calculated.

The concept of FL was introduced by Professor Zadeh at the University of California at Berkeley [5]. His goal was to develop a model that could more closely describe the natural language process. FL can be compared to the human decision making process. Conventional or classic logic is more like Boolean conditions (true/false). Fuzzy logic can be described as a superset of Boolean logic, having its own similarities and differences with Boolean algebra.

2.1.3.2 Structure

The structure of a Fuzzy system consists of:

- Rule base: the set of fuzzy rules are selected
- Database: defines the membership functions that are going to be used in the fuzzy rules
- Reasoning mechanism: derives a conclusion from facts and rules (inference procedure).

Membership Functions

The membership function represents the degree of truth as an extension of valuation. The degree of truth is often confused with probabilities. Probability is the likelihood that something is true. FL is the degree to which something is true (or within a membership set). A fuzzy set A on a universe of discourse U* is characterized by a membership function, $\mu_A(x)$ that takes values between [0, 1]. A membership function is essentially a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.

The four major types of membership functions are triangular, trapezoidal, Gaussian and generalized bell [36].

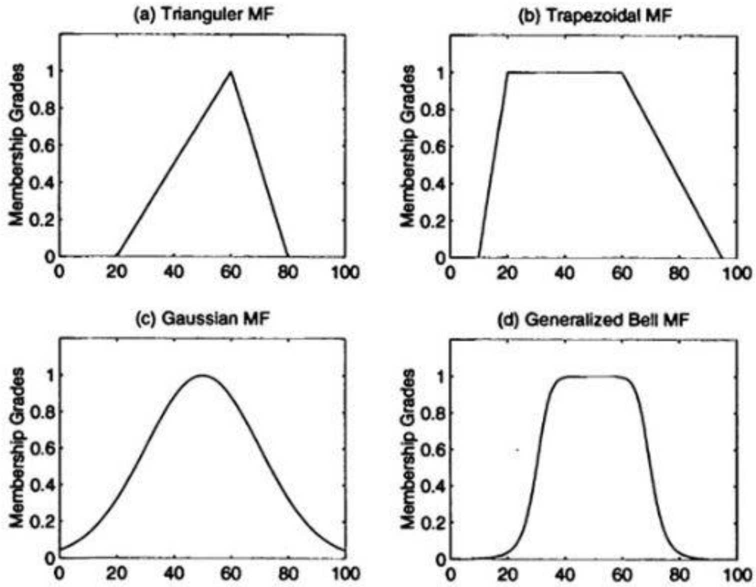


Fig.2.4: Membership functions

The basic rules of membership functions are:

- Each point of each input should at least belong to one membership function.
- The sum of two overlapping membership functions should not exceed 1.
- The accuracy of the fuzzy system can be raised by increasing the number of membership functions, but this has a drawback on the stability of the control system.

Fuzzy if-then Rules

The fuzzy if-then rules or fuzzy conditional statements are expressions of the form IF x THEN y, where x and y are variables of fuzzy sets. Due to their concise form, fuzzy if-then rules are often employed to capture the imprecise modes of reasoning that play an essential role in the human ability to make decisions in an environment of uncertainty and imprecision. An example that describes a simple if-then rule is the following:

If x is high, then y is low.

Where x and y are linguistic variables and high and low are linguistic labels, that are characterized by membership functions.

Logical Operations

In fuzzy logic, operators such as AND, OR, and NOT are implemented by intersection, union, and complement operators. These operators can be defined by many ways. Generally, AND, OR, and NOT operators are implemented by the min, max, and complement operators.

<u>Fuzzy Inference System (FIS)</u>

A fuzzy inference system (FIS) maps inputs to outputs. A FIS consists of four components: the fuzzifier, inference engine, rule base, and defuzzifier [38]:

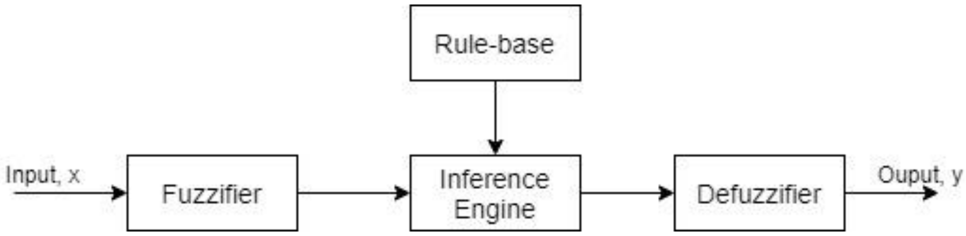


Fig.2.5: Block diagram of FIS

The fuzzifier maps input numbers into corresponding fuzzy membership values. The inference engine defines the mapping from input fuzzy sets to output fuzzy sets. Plus, it determines the degree to which the antecedent part is satisfied for each rule. If the antecedent part of the rule has more than one clause, then fuzzy operators are applied to obtain a number that represents the result of the antecedent part for that rule. Outputs of all rules are then aggregated. The defuzzifier maps the output fuzzy sets into a number. Several methods for defuzzification are used in practice, including the mean of maxima, maximum, centroid, height, and modified height defuzzifier. The most popular defuzzification method is the centroid, which calculates and returns the centre of gravity of the aggregated fuzzy set. The rule base contains linguistic rules that either are provided by experts or are extracted from the numerical data. The FIS can be viewed as a system that depicts an input vector to an output vector, once the rules have been established. Fuzzy rules are fired in parallel, and that is one of the most important aspects of FIS. In FIS, there is no connection between the order in which rules are fired and the output.

2.1.3.3 Advantages and Limitations

The main advantages of Fuzzy Logic are:

- FL imitates human decision making to handle vague concepts.
- Computation is faster due to intrinsic parallel processing nature (decreasing the design time of the problem).
- FL has the ability to deal with imprecise information.
- Modeling of complex, non-linear problems.
- Can deal with real-world, ambiguous problems. FL is mathematically oriented, but also at the same time emphasizes ambiguity and uncertainty.
- Approximation of any continuous function to a precision of any degree by membership functions and rules.
- FL simplifies design complexity by using experience and knowledge in simple linguistic like rules. The relation between input and output is not modeled by complex math equations and can be easily be used without any previous knowledge.

The main limitations of Fuzzy Logic are:

- Highly abstract and heuristic.
- Requires expertise for rule discovery (data relationships).
- Lack of the self-organizing and self-tuning mechanisms of neural networks.
- FL is not always accurate. The results are perceived as guesses, so cannot be as widely trusted as that of classical logic.
- FL is often confused with probability theory. The terms are used interchangeably while they are not the same. Probability is the likelihood that something is true. Fuzzy logic is the degree to which something is true.
- Low respectability of FL is a major problem. Though fuzzy logic is the superset of all logic, it has not been widely accepted as classical logic because of the lack of precision.

2.1.4 ANFIS

2.1.4.1 Introduction and Historical Background

ANFIS is a kind of artificial neural network that is based on the Takagi-Sugeno fuzzy inference system. Single NNs is lack the performance not needed in order to provide the heuristic knowledge for the prediction of battery's SOC. Therefore, it is not appropriate to express the knowledge based on the rules or to make use of the existing experience and work. These drawbacks lead to the increase of network's training time. A single fuzzy predictive model can simply realize the learning heuristic knowledge but can't get the accurate result. It is difficult to automatically form and adjust the fuzzy rules of membership functions. This occurs as the model's self-learning performance and adaptive capacity is weak. Combination of NN and FL systems can get the exact value in any condition.

The roots of the creation of ANFIS begun when Chiu proposed a method for the selection of inputs of the neuro-fuzzy model built for nonlinear system identification. Ishibuchi implemented a routine, in which the neural network is trained by utilizing the numerical data as well as expert human knowledge that is represented by the fuzzy if and then rules. Juang and Lin presented a method for the identification of a dynamic system with the help of a Takagi-Sugeno-Kang type fuzzy rule-based model, which also possesses the learning ability of a neural network. Jang developed a simple technique for the selection of inputs in the identification of a nonlinear system. ANFIS is one of the most successful systems developed by Jang, which applies neural learning rules to identify and tune the parameters and structure of a fuzzy inference system, based only on the available data.

2.1.4.2 Structure

ANFIS is an adaptive network based on a Sugeno type fuzzy inference system. It can simulate and analyze mapping relations between the input and output data through a learning algorithm, designed to optimize the given parameters. It combines the benefits of artificial neural networks and FISs in a single model. Additionally, ANFIS has accurate learning and generalization capabilities, which derive from the semantically meaningful fuzzy rules and membership functions. To illustrate a first order Takagi-Sugeno ANFIS, a FIS with two inputs (x and y) and one output is considered where each input is assumed to have two fuzzy sets [38].

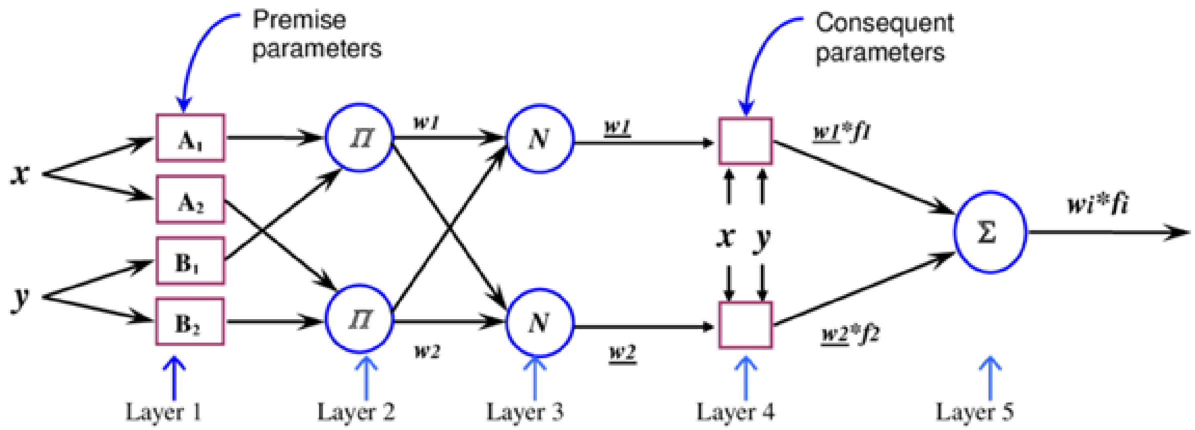


Fig.2.6: Structure of 1st order TS ANFIS

The ANFIS architecture has five layers where nodes in each layer have different functionality. The rectangle nodes are called adaptive nodes, because they have parameters that can be modified, and the circular ones are called fixed nodes. The 'Π' letter is used for multiplication, the 'N' for normalization and the 'Σ' for summation. In addition, there are only directional links through nodes.

Layer 1: The output of the node is the degree to which the given input satisfies the linguistic label of the node (A, B). There are different membership functions (μ_A, μ_B) (always between 0 & 1) that can be used, e.g. bell-shape (where $\chi \equiv \chi_1$):

$$A_i(x_1) = \left[1 + \left(\frac{x_1 - a_{i1}}{d_{i1}}\right)^2\right]^{-1}$$

Where a, d are so-called premise parameters of the membership function and they change the shape of the bell.

Layer 2: Computation of firing strength (w) of the associated rule using And-Or-Not logic.

$$w_i = \mu_A(x)\, X\, \mu_B(y)$$

Layer 3: Normalization of firing strengths.

$$\overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1, 2$$

Layer 4: The outputs of these nodes are the product of Layer 3 and the individual rule output of associated rule. For example:

Rule 1: If x is A_1 and y is B_1 then $z_1 = p_1 * x + q_1 * y + r_1$

Where p, q, r are so-called consequent parameters

$$\overline{w_i} z_i = \overline{w_i}(p_i x + q_i y + r_i)$$

Layer 5: Compute the overall system output

$$\sum_{i=1}^{2} \overline{w_i} z_i$$

The task of ANFIS in learning is to tune the premise and consequent parameters until the desired input-output mapping from the FIS is achieved. This learning task is accomplished by a hybrid algorithm combining the least squares method and the gradient descent method which is explained in the following section.

Back Propagation

Requires three things:

1) A dataset consisting of input-output pairs (x_i, y_i), where x_i the input is and y_i is the desired output of the network on input x_i. The set of input-output pairs of size N is denoted $X = \{(x_1, y_1),\ldots,(x_N, y_N)\}$.

2) A feed forward neural network whose parameters are collectively denoted θ. In back propagation, the parameters of primary interest are w_{ij}^{k}, the weight between node j in layer l_k and node i in layer l_{k-1}, and b_i^k, the bias for node i in layer l_k. There are no connections between nodes in the same layer and layers are fully connected.

3) An error function, $E(X, \theta)$, which defines the error between the desired output y_i and the calculated output of the neural network on input x_i for a set of input-output pairs $(x_i, y_i) \in X$ and a particular value of the parameters θ.

Least Square Method

The least square method [27] is a form of mathematical regression analysis used to determine the line of best fit for a set of data, providing a visual demonstration of the relationship between the data points. Each point of data represents the relationship between a known independent variable and an unknown dependent variable. Given data {(x1, y1), . . . ,(xN , yN)}, the error should be defined, associated to saying y = ax + b, by

$$E(a,b) = \sum_{n=1}^{N} (y_n - (ax_n + b))^2$$

The goal is to find values of a and b that minimize the error. In multivariable calculus this requires the values of (a, b) to be found, such that

$$\frac{\partial E}{\partial a} = 0, \quad \frac{\partial E}{\partial b} = 0$$

Hybrid Learning

The learning algorithm for ANFIS is a hybrid algorithm which is a combination of the gradient descent and least-squares. Specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backwards and the premise parameters are updated by gradient descent. The consequent parameters are identified as being optimal under the condition that the premise parameters are fixed. Accordingly, the hybrid approach converges much faster since it reduces the search space dimensions of the original pure back propagation method [39] [42].

	Forward Pass	**Backward Pass**
Premise Parameters	Fixed	Gradient Descent
Consequent Parameters	Least Square estimation	Fixed
Signals	Node Outputs	Error Rates

Table.2.1: Forward and Backward passes in the hybrid learning procedure for ANFIS

Performance Criteria

In this thesis, the root mean square error (RMSE) is used to determine the error between the simulated and the experimental data [42]. It is defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1=1}^{n}(a_i - p_i)^2}$$

Where a_i and P_i are the actual and predicted values, respectively. The smaller RMSE value implies a better performance.

2.1.4.3 Advantages and Limitations

In addition to the general advantages of the NN and FL, ANFIS networks present interesting advantages. These advantages result from the fact that ANFIS presents a much more specific mathematical structure which allows it to be used as a good universal adaptive approximator. The most significant advantages of ANFIS are:

- Much better learning ability: for a similar network complexity, a much smaller convergence error is achieved. The slow convergence is compensated by the fact that the error in ANFIS is small.
- ANFIS can achieve highly nonlinear mapping compared to other common linear methods of similar complexity.
- ANFIS requires fewer adjustable parameters in comparison to those required in NN structures.
- The ANFIS structure gives the opportunity of parallel computation.
- The fuzzy rules allow for easier model understanding and/or interpetation, in other words well-structured knowledge representation.
- Better integration with other control design methods.
- Easy incorporation of both linguistic and numeric knowledge for problem solving.

On the other hand there are some major drawbacks as well:

- ANFIS translates prior knowledge into network topology and initial fuzzy partitions.
- Sensitivity to initial number of partitions. For example, high partition number can cause surface oscillations around points.
- Exponential complexity in some applications.

2.2 THE BATTERY SYSTEM

2.2.1 Introduction

Power systems always face serious challenges, some examples being the depletion of fossil fuels, integration of renewables environmental obligation, electricity market, hybrid electric vehicles, demand response and smart grids. Along the same line, energy storage systems are a necessity in order to maintain supply and demand balance as well as provide ancillary services for power systems. Electric energy storage systems are widely used in hybrid electric vehicles and systems working isolated from the grid, with batteries being one of the most popular [41]. A battery is an electrochemical device that achieves the conversion from the chemical energy contained in its active materials directly into electrical energy. The reversal of this process leads the battery to be recharged. The previous technique is used in automotive rechargeable systems. While the term “battery” is commonly used, the basic electrochemical unit is the “cell”. A battery consists of one or more of these cells, connected in series or parallel, or both. The type of connection has an impact on the desired output voltage and capacity. An important distinction that can be made along batteries is between primary and secondary batteries. Primary batteries are non-rechargeable, whereas secondary batteries are rechargeable. Different battery systems are available for both primary and secondary batteries. Each battery system is characterized by its chemistry. Examples of primary batteries are zinc-carbon (also known as alkaline batteries) and mercuric-oxide. Examples of secondary batteries are sealed lead-acid (SLA) , NiCd, NiMH batteries. The focus in this thesis will be on secondary batteries and especially lithium ion. Note that some battery systems are available in both a non-rechargeable and a rechargeable form, such as zinc-alkaline-MnO2 batteries. The battery is an electrochemical device with an extremely complex behavior and its distinct nonlinear behavior depend on several internal and external conditions. As a result, estimating their state of charge is a challenging task. Considering the complexity and difficulties of the battery, several important data will be chosen, in order to achieve an impact on its behaviour. In that case the accuracy of the estimated SOC value will have a measurable effect on the optimization of the charging and discharging of the battery.

2.2.2 Historical Overview

Batteries have been around for a long time. Luigi Galvani and Alessandro Volta are closely associated with the development of batteries and the related science of electrochemistry. Galvani performed an experiment in 1790, in which he suspended a frog from an iron hook. With a copper probe he measured electric pulses, which he believed originated in contractions of the muscles of the frog’s legs. Volta attributed these contractions to the current flowing between the iron and copper metals. To prove that current could flow between two metals with an electrolyte in between, he built a ‘pile’ consisting of alternating silver and zinc plates interleaved with paper or cloth, which was soaked with an electrolyte. Hence, Volta was the first person in modern times to have built an actual battery. On the basis of Volta’s work, other scientists also developed batteries of various designs. A recurring problem with these batteries was gas formation at the electrodes. Gaston Planté investigated the behaviour of various metals in various electrolytes, in particular diluted sulphuric acid. He constructed batteries as a sandwich of thin layers of lead, separated by sheets of coarse cloth in a cylindrical container filled with diluted sulphuric acid. In addition to the types of batteries mentioned so far, a wide variety of batteries have been developed since Volta’s ‘pile’, both rechargeable and non-rechargeable. The advances in the evolution of portable electronic systems have had a significant effect on the development of new types of batteries. However, only fairly little progress has been made in improving battery characteristics such as energy density, shelf life and reliability in comparison to the advances made in electronic circuits. The introduction of the nickel-metal hydride (NiMH) battery in 1990 and the li-ion battery in 1991 were of great importance for portable consumer products. Apart from the continuous need for higher energy densities, environmental concerns have also boosted the development of these new types of batteries.

2.2.3 Battery Terminology

Some terms are essential for understanding the performance and characteristics of batteries and are explained in the following paragraphs [24][25].

Battery Condition

1. **Open-Circuit Voltage (OCV)**: The voltage between the positive and the negative electrodes when there is no load on the battery. The open-circuit voltage affects the battery state of charge. Specifically, an increase in the open-circuit voltage comes with an increase in battery SOC.
2. **Discharge Rate (C-rate)**: Discharge current is often expressed as a C-rate in order to normalize against battery capacity, which is different between batteries. A C-rate is a measure of the rate at which a battery is discharged relative to its maximum capacity. A 1C rate means that the discharge current will discharge the entire battery in 1 hour. The power output ability can be evaluated from the discharge rate.
3. **State of Charge (SOC)**: An expression of the present battery capacity as a percentage of maximum capacity. SOC is generally calculated using current integration to determine the change in battery capacity over time.
4. **State of Health (SOH)**: In general, SOH refers to the current state of health of the battery as compared to its beginning of life measurement. In other words, SOH is intended to indicate how long the battery will take to reach its end of life. It is a measure of internal resistance, capacity, voltage, self-discharge. Except from those, the battery's ability to accept charge and the total number of charge-discharge cycles that have completed at any point in time derived from state of health.
5. **Internal Resistance:** This is the total resistance of a battery between its two electrodes. Includes the resistance from current collectors, electrode and active materials, separators, and electrolytes. The smaller the internal resistance, the better the performance will be achieved. It is also dependent on the state of charge/discharge of a battery. When the internal resistance increases, the battery efficiency decreases, and thermal stability is reduced, plus the charging energy is converted into heat.
6. **Self-discharge**: This is a phenomenon in a battery in which internal chemical side reactions reduce the stored capacity of the battery without any connection between the electrodes. Self-discharge decreases the shelf life of batteries and causes them to initially have less than a full charge when actually put to use.

Battery Technical Specifications

1. **Nominal Voltage**: This refers to the average voltage during the total discharge process of a battery at the rate of 0.2C. Also known as the "normal" voltage of the battery.
2. **Cut-off Voltage:** The final voltage between two electrodes of a battery reached during a charge or discharge process. This is the minimum allowable voltage, and it generally defines the "empty" state of the battery.
3. **Discharge Curve**: The change of voltage with time during a discharge process.
4. **Nominal Capacity (Ah for a specific C-rate**): This refers to the total capacity available when the battery is discharged at a certain discharge current, specified as a

C-rate (e.g. 0.2 C). Capacity is calculated by multiplying the discharge current (in Amps) by the discharge time (in hours). Nominal capacity decreases with an increase in C-rate.

5. **Cycle Life**: This is the number of times that a rechargeable battery can be cycled (charged and discharged) before it loses its ability to accept charge. Cycle life is estimated for specific charge and discharge conditions. It is dependent on battery type, chemical composition, depth of discharge, cell design and it is affected by temperature and humidity.

2.2.4 Traditional Battery Characteristics

2.2.4.1 Introduction

A battery's actual rated capacity, besides on operational conditions (such as discharge rate and battery temperature), will strongly depend on its design. In general, the theoretical energy density, which relies on the battery chemistry, will be much larger than the energy density specified in a battery's data sheet. Most battery systems available on the market, whether cylindrical or prismatic and irrespective of their size, can be found in different types. These types have been optimized for use in specific applications. Examples are high-rate batteries, which allow relatively large discharge currents of up to several times the C-rate. Another application is high-temperature batteries which allow operation at higher temperatures. Last, are high-capacity and fast-charge batteries, which enable a very quick recharge. In addition, there is a wide range of different cell chemistries that offer different voltages, power and energy performances. The main characteristics of the most important secondary battery systems are summarized in the following sections.

2.2.4.2 NiCd

The Nickel Cadmium (NiCd) battery is commonly known as relatively cheap and robust. It is universal and can still be found in many portable devices today. Most NiCd batteries can supply large currents. It is possible to charge NiCd batteries in a relatively short period of time because of their robustness. Charge times of only 10 minutes and the average cell voltage is 1.2 V. Power tools usually use NiCd batteries, because of their high power delivery and short recharge times make. Other applications include portable audio products, cordless phones, camcorders and shavers.

Although very suitable for power tools, NiCd batteries have some drawbacks. First of all, their energy density and specific energy are relatively low. Secondly, NiCd batteries suffer from the so-called memory effect. This effect can be defined as a decline in effective capacity with repeated partial charge/discharge cycles. Eventually, the battery will only be able to supply the capacity retrieved from the partial cycling. The battery voltage drops significantly and most portable devices will stop functioning at that moment. As a final drawback, the use of cadmium in NiCd batteries involves serious environmental problems [20].

2.2.4.3 NiMH

Nickel Metal Hydride (NiMH) cells use nickel hydroxide $Ni(OH)_2$ for the cathode. Hydrogen is used as an active element in a hydrogen-absorbing anode. This electrode is made from a metal hydride, usually alloys of lanthanum and rare earths that serve as a solid source of reduced hydrogen that can be oxidized to form protons. The electrolyte is alkaline, usually potassium hydroxide. NiMH cells have higher energy density than nickel-cadmium cells, rapid recharge capability, long cycle life and long shelf life in any state of charge. There are minimal environmental problems.

However, its high-rate performance is less than that of nickel-cadmium. Other drawbacks are the poor charge retention, memory effect and higher cost anodes. It has been used in computers, cellular phones and other consumer electronic applications. NiMH should not be used in applications where low battery cost is the major consideration. It was the main choice for hybrid electric vehicles. However, lithium-ion batteries are gradually taking their place [21].

2.2.4.4 Lead Acid

Lead-acid batteries are composed of a Lead-dioxide cathode. The typical cell voltage is 2 Volts. Lead acid is a popular low-cost secondary battery, available in large quantities and in a variety of sizes and designs. Furthermore, it has good high-rate performance, moderately good low and high temperature performance, easy state of charge indication and good charge retention for intermittent charge applications. Cell components are easily recycled. Because of the irreversible physical changes in the electrodes, failure occurs between several hundred and 2,000 cycles.

The main drawbacks of these batteries are their comparatively low energy density, long charging time and the need for careful maintenance. It still dominates the stop-start battery and e-bike battery market. The heavy metal element makes lead acid toxic and improper disposal can be hazardous to the environment. The lead acid battery with continuous improvement will remain competitive [23].

2.2.4.5 Lithium-Ion

The chemistry of Li-ion batteries differs significantly from that of Ni-based batteries. Li-ion cells offer the advantage of a high average operating cell voltage of 3.6 V, because of the very negative standard potential of lithium with respect to the standard hydrogen reference electrode. Moreover, Li-ion batteries have a relatively high specific energy, which results in batteries that are lighter than Ni-based batteries at the same capacity. For further performance improvements there have been many efforts in solid state chemistry. This includes increase in energy density, rate capability and the ability to provide high power, as well as long cycle life and thermal stability for increased safety. Moreover, fast charge capabilities as well as cost reduction have been achieved. The aforementioned accomplishments were achieved through the use of inexpensive raw materials synthetic processes and materials of low toxicity and environmental banality. Applications include notebook computers, camcorders and phones.

On the other hand, there are also some drawbacks. Lithium ions are brittle. To maintain the safe operation of these batteries, they require a protective device to be built into each pack. This device, also referred to as the battery management system, limits the peak voltage of each cell during charging and prevents the cell voltage from dropping below a threshold during discharging. Controlling the maximum charging and discharging currents and monitors the cell temperature are also important [22].

2.2.4.6 Conclusions

Lithium is the lightest metal with the greatest electrochemical potential and the largest energy density per weight of all metals found in nature. Such rechargeable batteries could provide high voltage, excellent capacity and a remarkably high-energy density. However, lithium is inherently unstable. Nevertheless, certain precautions should be made during charging and discharging. That is why an algorithm for better charging and discharging for melioration battery life and aging is presented in this thesis.

Battery	**NiCd**	**NiMH**	**Li-ion**	**Li-poly**	**Lead Acid**
Energy density (Wh/l)	90-150	160-310	200-300	200-250	90-160
Specific Energy (Wh/kg)	30-60	50-90	90-115	100-115	30-50
Fast charge time	1h	2-4h	2-4h	2-4h	8-15h
Cycle life	300-700	300-600	500-1000	200	200-300
Cost per cycle(dollar)	0.04	0.12	0.14	0.29	0.10

Table.2.2: Overview of the main characteristics of Batteries

CHAPTER 3: BATTERY CHARGING, DISCHARGING AND HYBRID ELECTRIC VEHICLE OPERATION MODELLING

3.1 Definition of the System

3.1.1 Charging and Discharging Operation Sub-System

Not all charging and discharging methods are suitable for li-ion batteries due to their sensitivity to overheating and under/over voltage. Compared to other technologies, the amount of parasitic processes is low, thus minimizing the benefits of using more complex charging methods. For example, pulse charging would minimize the gas forming in a cell, but this is not a problem in the li-ion. Overcharging is wasteful and damages both li-ion batteries and other technologies that are connected with them.

Charging can be done at different rates. When considering charging operation methods for data acquisition, the most common is slow charge. In this thesis, an equivalent charging operation circuit model for battery was developed in MATLAB/Simulink [shown in Figure 3.1] [32][33].

MATLAB/Simulink is a powerful simulation program for circuit and system designs. It provides a lot of simple, powerful and user friendly tool boxes and simulation blocks.

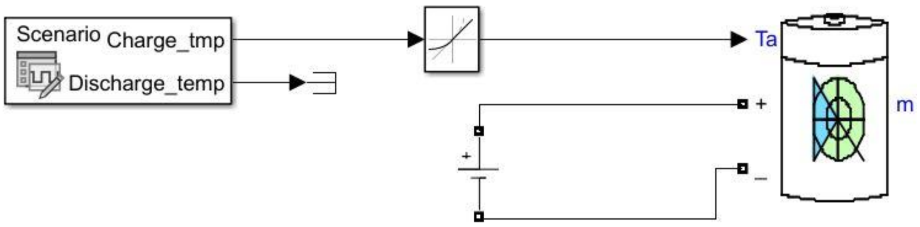


Fig.3.1: Equivalent Charging Operation Circuit Model

The model circuit consists of a dc voltage source (5 V), a Lithium-Ion (LiFePO4) battery (3.3 V, 2.3 Ah), a rate limiter and a block that represents the ambient temperature.

Moreover, management of the battery is necessary to avoid battery from being over-discharged. Therefore, an accurate battery model in discharge operation mode is vital to forecast the characteristics of the battery [32] [33].

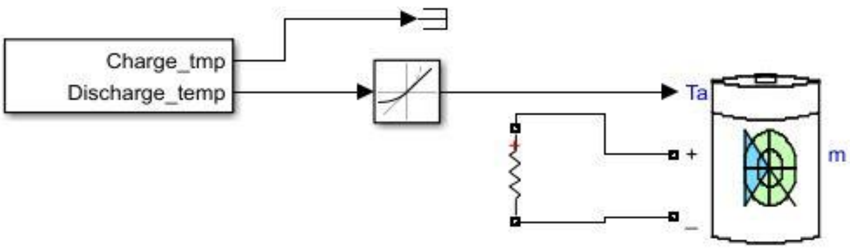


Fig.3.2: Equivalent Discharging Operation Circuit Model

The model circuit consists of a Resistance Branch (5 Ohm), a Lithium-Ion (LiFePO4) battery (3.3 V, 2.3 Ah), a rate limiter and a block that represents the ambient temperature.

The rate limiter limits the rising and falling rates of signal. This is beneficial to the simulation time and to obtain better data for ANFIS. The rising and falling slew rate were set to 0.5 and -0.5 respectively.

In order to represent the ambient temperature, two signals were created with random values between -5 Celsius and 28 Celsius, varying throughout the entire simulation time.

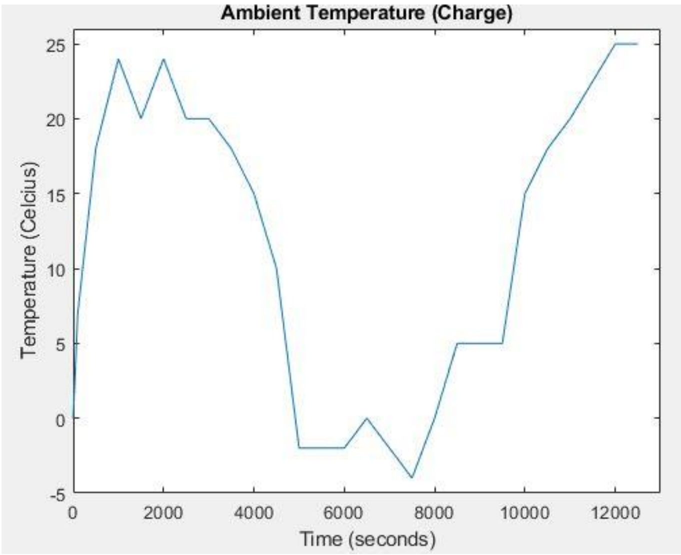


Fig.3.3: Ambient Temperature for Charging Operation System

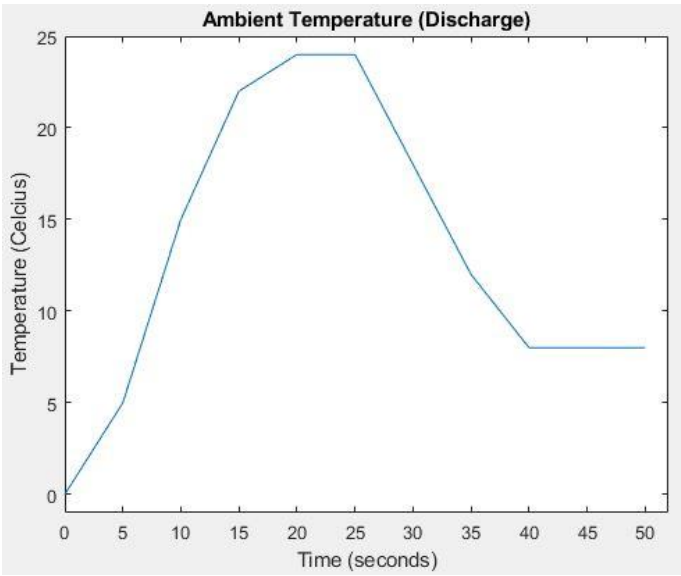


Fig.3.4: Ambient Temperature for Discharging Operation System

3.1.2 Hybrid Electric Vehicle Operation Sub-System

Essential functions such as lighting, instrumentation and windshield wipers are necessary for the safety of a car. These features, however, consume energy and therefore the performance in long run when used in a hybrid electric vehicle (HEV) may decrease [29]. In addition, temperature, heating and air-conditioning for are also important factors that affect the battery. Other functionalities in modern cars are power steering, electrical windows, front and rear window defrost, media functions, door looks etc. All functions need to be considered when constructing a battery for an electrical vehicle. So SOC estimation, in real world driving conditions, is a critical issue. Experimental battery tests were conducted using MATLAB-Simulink programming environment. The hybrid electric vehicle operation model is based on Mitsubishi i-MiEV [29].

HEV design is comparable when crossing a certain distance, according to predefined driving dynamics, starting with the full capacity of the battery. Multiple standardized driving cycles exist, and in this thesis Federal Test Procedure (FTP-75) is used [26]. The characteristics are:

- Distance travelled: 17.77 km (11.04 miles)
- Duration: 1874 seconds
- Average speed: 34.1 km/h (21.2 mph)

The procedure is updated by adding the "hot start" that repeats the "cold start" (phase of 505 seconds) of the beginning of the cycle. Schematic representation of a cycle of FTP-75 is shown in Fig.3.5 [29].

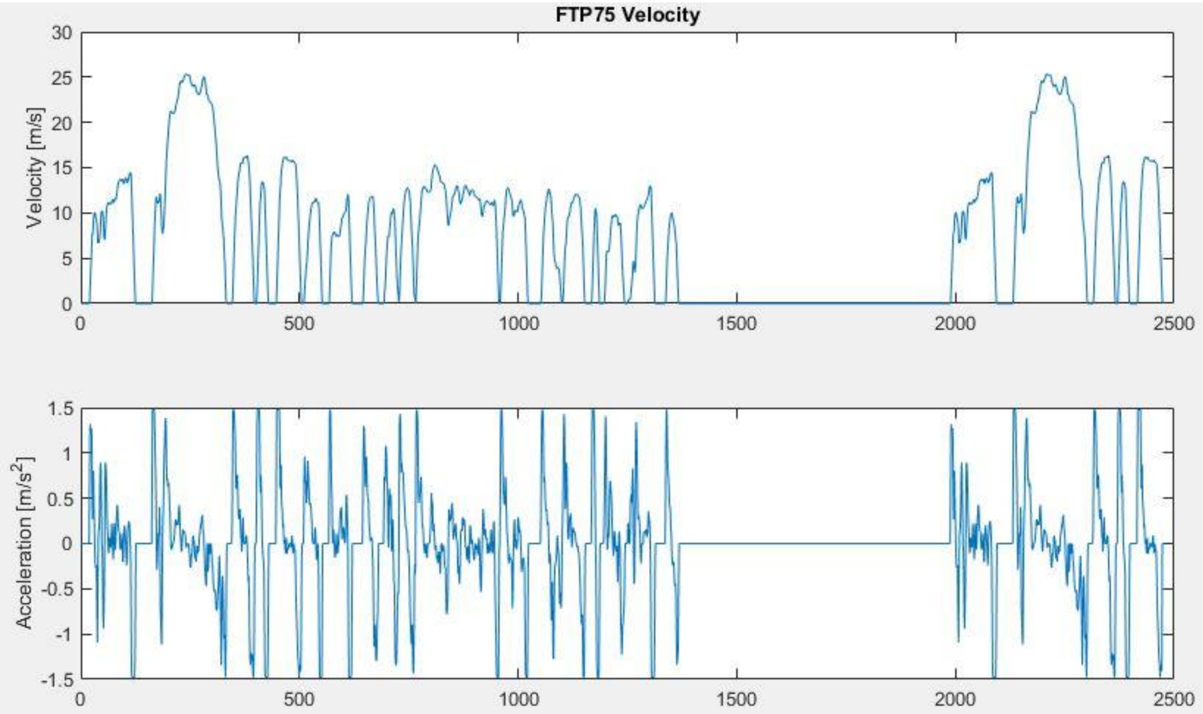


Fig.3.5: Acceleration and Velocity for FTP75

The calculation of the necessary energy is based on the driving mode and the basic parameters of the HEV. This energy is transferred through electric drive and is considered as the electrical load of the battery (discharge - acceleration and driving, charge - recovery of braking energy). For simplicity, this thesis does not take into account any losses of energy within the vehicle (losses of control electronics, transmission losses or losses of the electric motor), which in real case may reach up to 20%.

The total resistance force of the vehicle movement consists of three components: rolling resistance, air resistance, and gradients resistance.

$$Air\ resistance\ force = \frac{1}{2} * C * A * p * u^2$$

$$Rolling\ resistance\ force = \mu * m * g$$

$$Gradient\ resistance\ force = m * a * \delta$$

Where C: is the drag coefficient (0.0425), A: vehicle projected area (0.116 m/s^2), p: air density (1.2 kg/m^3), μ: coefficient of rolling friction (0.013), m: the mass of car (dead weight and mass of load), g: gravitational forces (9.8 m/s^2), δ: transmission coefficient (1.03), u reference speed and a: reference acceleration [29].

Each component is individually modeled in Simulink. Afterwards, they were united in a shared subsystem. In addition, a Matlab script was created in order to trim the signal (as shown in Fig.3.7). So, it can eventually be used as load to a battery and not to a battery pack [34].

It is worth noting that a controlled voltage source was used for the system implementation. This kind of source converts a signal (the load from the hybrid electric vehicle operation) into an equivalent voltage source in order to be connected to the battery (Fig.3.6). The proposed system of the hybrid electric vehicle operation was based on [29].

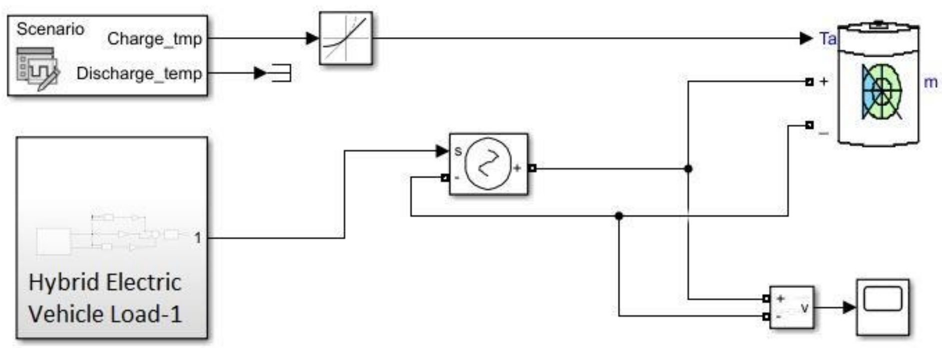


Fig.3.6: Hybrid Electric Vehicle Operation System

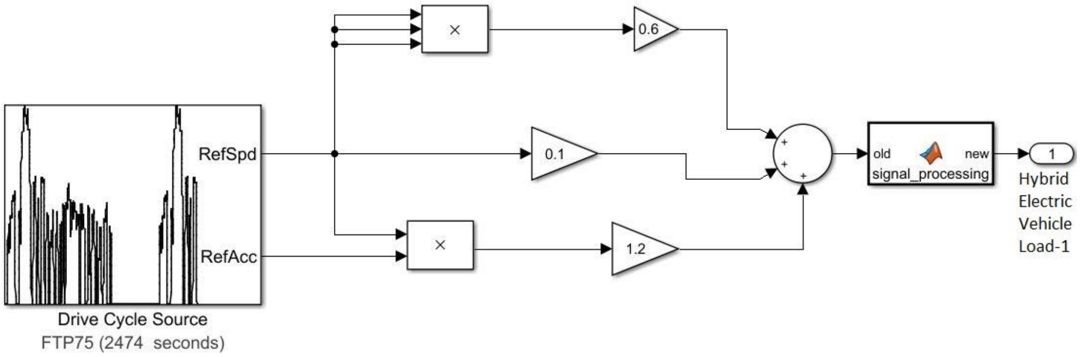


Fig.3.7: Hybrid Electric Vehicle Operation

3.1.3 Lithium-Ion Battery

An accurate model representing the characteristics of the battery is essential for SOC estimation accuracy. The battery can be implemented as a sum of complex models that reproduce the electrochemical reactions inside the battery, which requires a very high computational effort. Another implementation consists of simple models like the coulomb counting that have very good run-time performance but can be very imprecise. This happens due to error accumulation from current measurements. For the purpose of modeling the battery, Matlab software was used. In Matlab's graphical editor Simulink, a generic model of Lithium-Ion battery according to Shepherd's model is developed and verified [30][31].

Name of the Battery Parameter	Value of the Battery Parameter
Initial State of Charge	80 (%)
Response Time	70 (s)
Maximum Capacity	2.3 (Ah)
Cut-off Voltage	2.475 (V)
Internal Resistance	0.014 (Ohms)
Initial Cell Temperature	20 (deg. C)

Table.3.1:Battery Parameters

The equivalent circuit, which models in Matlab/Simulink the battery block subsystem, is:

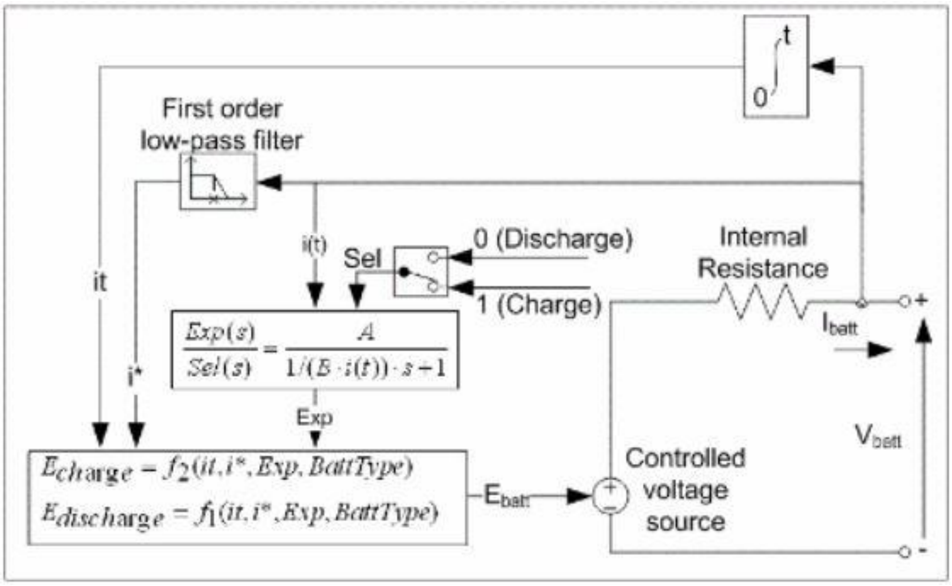


Fig.3.8: The battery subsystem

The typical discharge characteristics of Lithium-Ion battery are shown in Fig3.9 [31]. The characteristics can be separated into three areas. The exponential area that represents battery voltage overshoots above the nominal value. The operating point of the battery is in this area during a period of establishing a stationary value of discharge current after no load battery mode. In the nominal area of the battery operation, during the discharge mode, the voltage is slightly changed. When the nominal capacity of the battery power is discharged, it is followed by the third area of operation in which the battery voltage rapidly decreases.

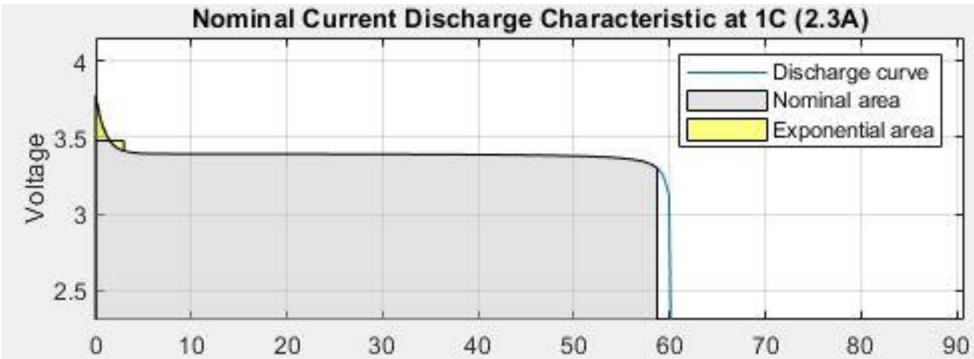


Fig.3.9: Discharge of Li-Ion at nominal discharge current

Simulink gives the opportunity to plot the changes of discharge characteristics at different currents.

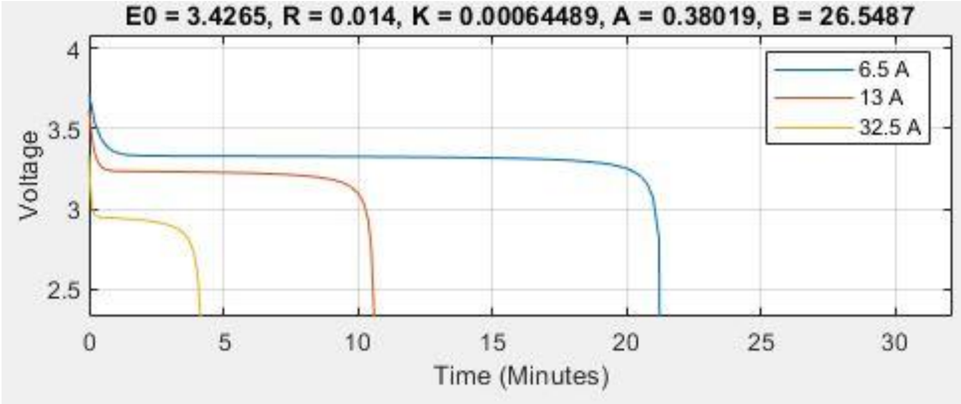


Fig.3.10: Discharge of Li-Ion at different currents

When the battery current is negative, the battery recharges. Following a charge characteristic is presented [31]:

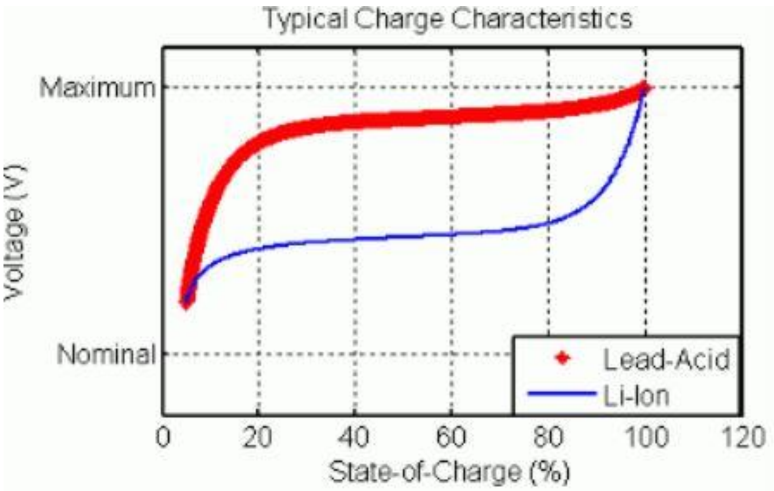


Fig.3.11: Charge of Li-Ion and Lead-Acid

It should be noted that operation of the Lithium-Ion battery, in the areas where a rapid voltage changes are present, requires the use of complex power electronic systems in order to protect the battery from overheating and destruction.

3.2 Experimental Data

In this study, the experimental data were derived from running simulations of the sub-systems that were previously mentioned in Section 3.1. The whole test was implemented on Matlab/Simulink. Firstly, we extract the data into three matrices (battery charging, discharging and hybrid electric vehicle operation).

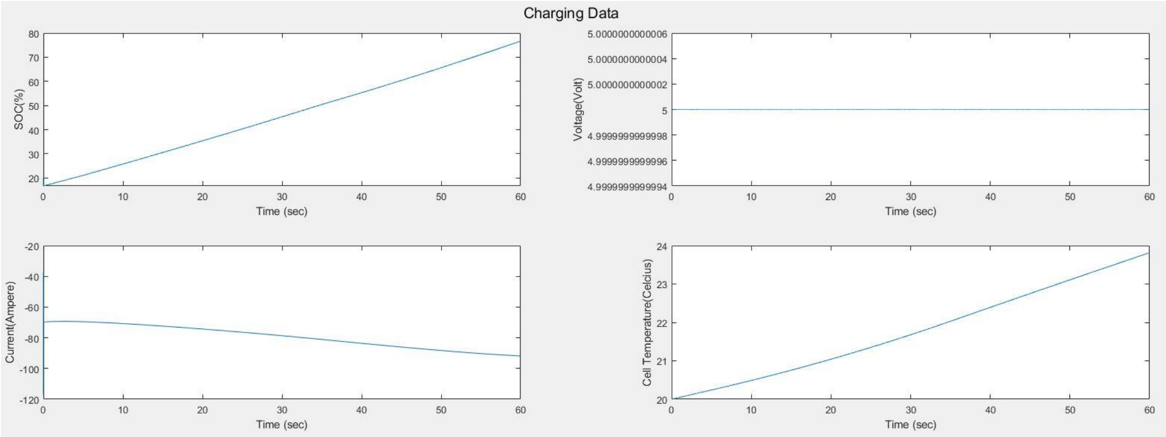


Fig.3.12:Data from Charging Operation System

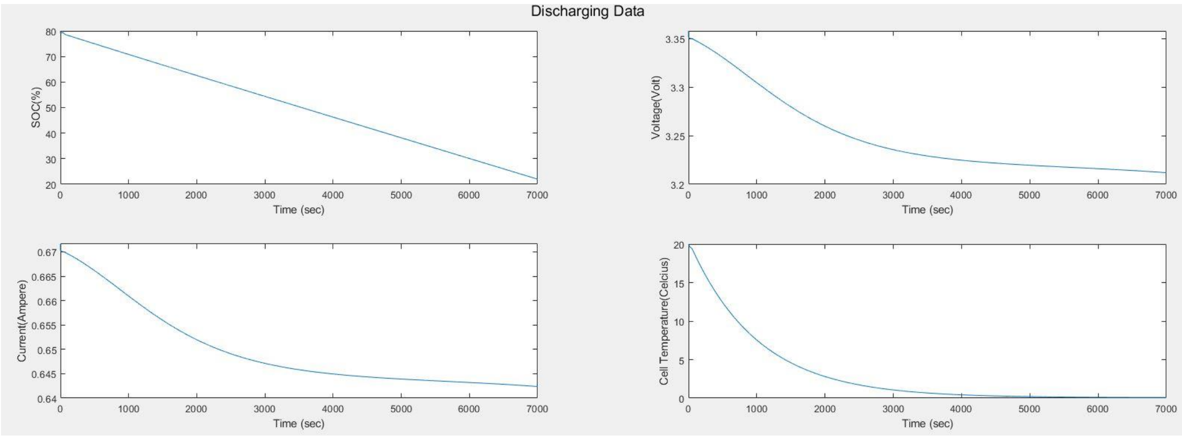


Fig.3.13:Data from Discharging Operation System

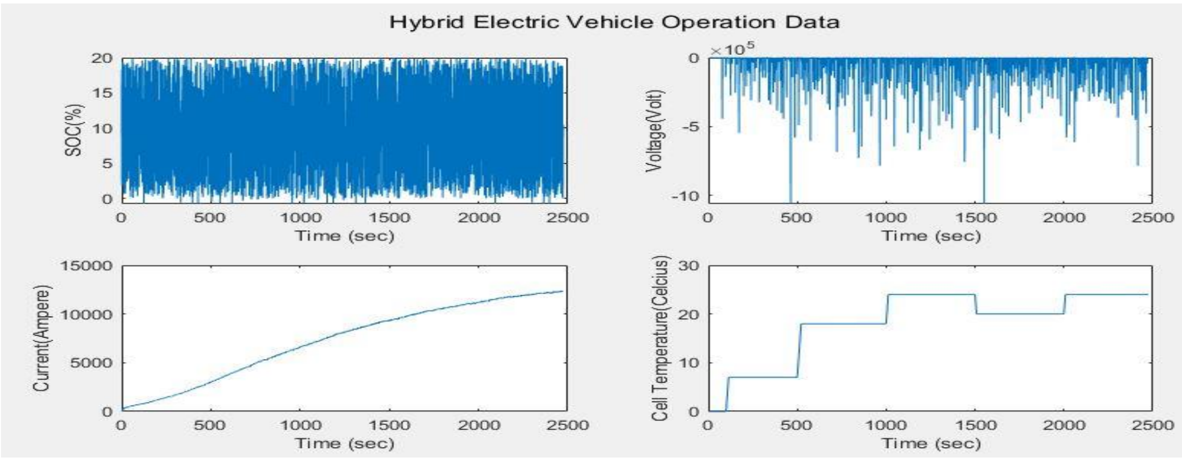


Fig.3.14: Data from Hybrid Electric Vehicle Operation System

To avoid over fitting problems during the estimation, each data set was randomly split into two sets: a training data set (70% of the data) and a validation data set (30%). The validation data set includes the testing data set (15%) and the checking data set (15%). The first one checks the generalization capability of resulting ANFIS and the second controls the potential of the model over fitting the data. Both data sets (testing and checking) were different from the training data set.

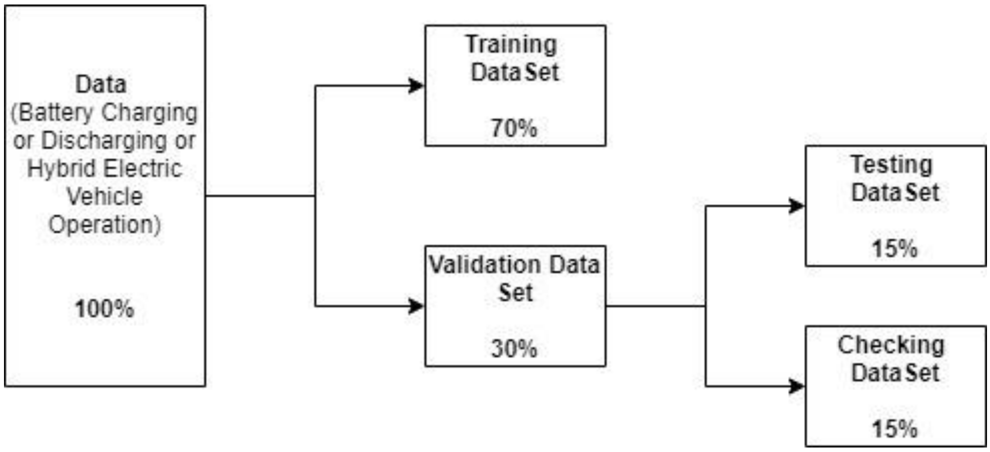


Fig.3.15: Data split

CHAPTER 4: PROPOSED ANFIS MODEL AND MYANFIS MODEL

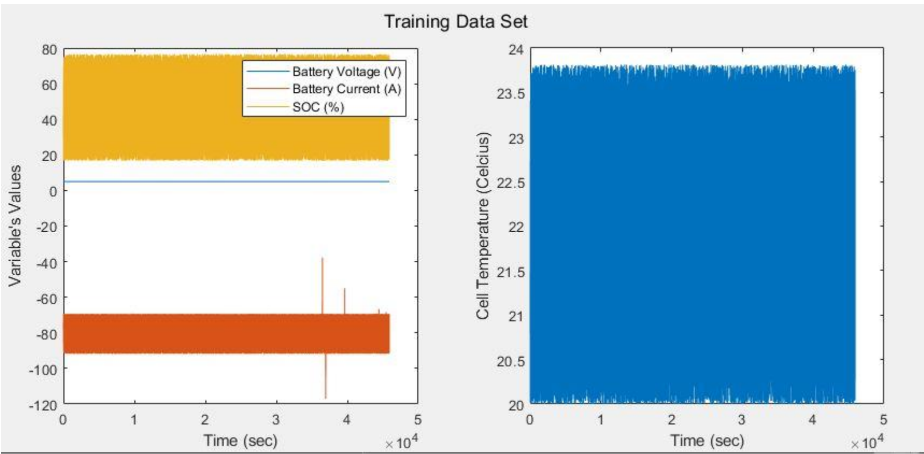
4.1 Input Data Selection

An excessive number of inputs may not only impair the transparency of the underlying model, but also increases the complexity of the computations necessary for building the model. Therefore it is necessary to determine the input variables.

Due to the complex nonlinear behavior of battery, SOC is determined by many factors. For example discharging current, discharging time and battery terminal voltage. Some other variables, that are usually used to improve the prediction accuracy, derive from the aforementioned factors by averaging, integrating and differentiating. Next, we must consider how varying temperatures affect the battery. The impact varies depending on if the battery is simply stored or also charged or discharged at high or low temperatures respectively. So, knowledge of the SOC of the battery is crucial when predicting performance of a battery on a certain temperature level.

There have been many methods to determine input variables. Techniques such as sensitivity analysis, genetic algorithm and statistical techniques (correlation analysis) are more commonly used. In this work, the input data are consisted of: voltage, current of the battery, cell temperature and the current value of state of charge. On the other hand, the only output being state of charge. These were selected according to [13], in which partial, linear and nonparametric correlation analysis have been tested.

<u>Charging Operation</u>



<u>Fig.4.1: Training Data Set (Charging Operation)</u>

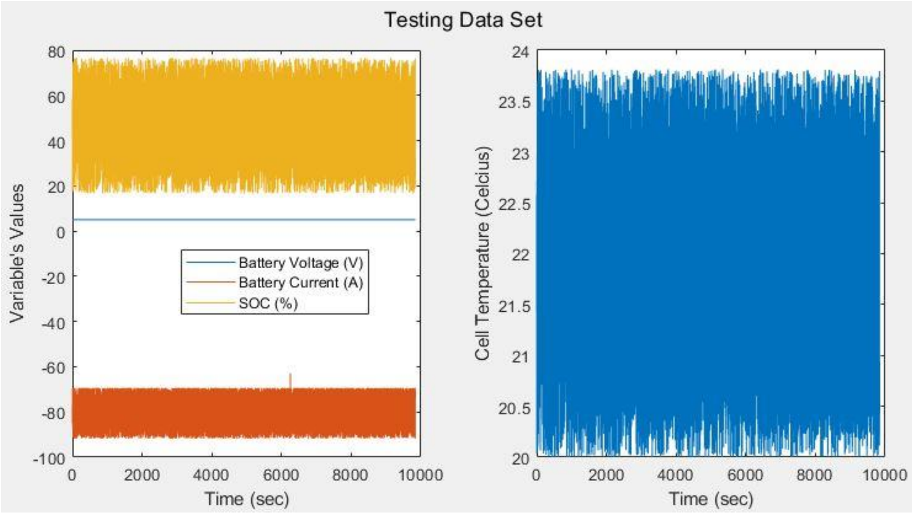


Fig.4.2: Testing Data Set (Charging Operation)

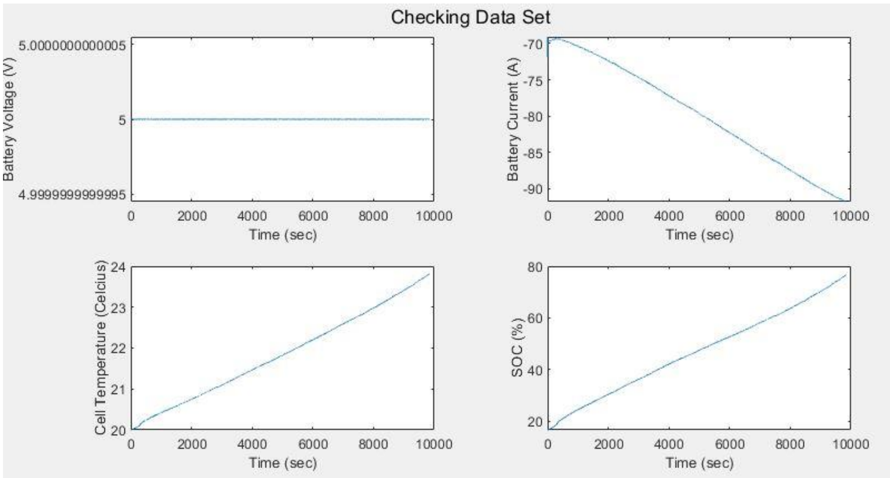


Fig.4.3: Checking Data Set (Charging Operation)

Discharging Operation

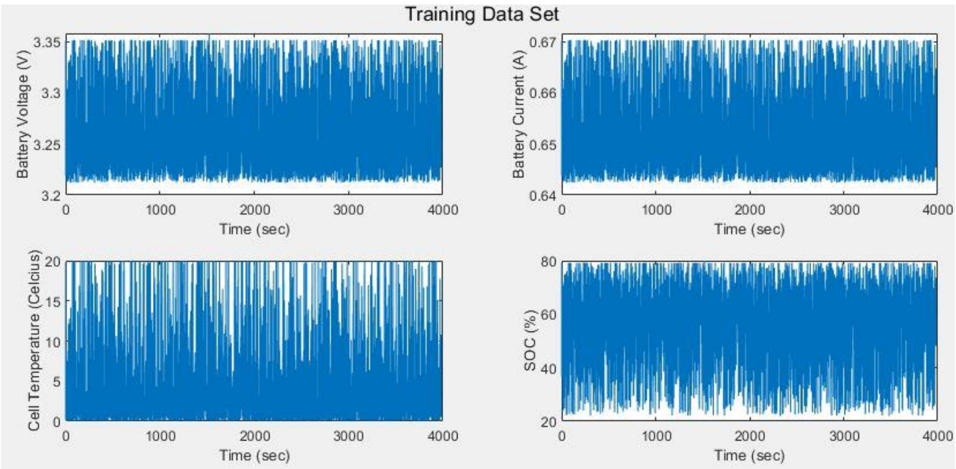


Fig.4.4: Training Data Set (Discharging Operation)

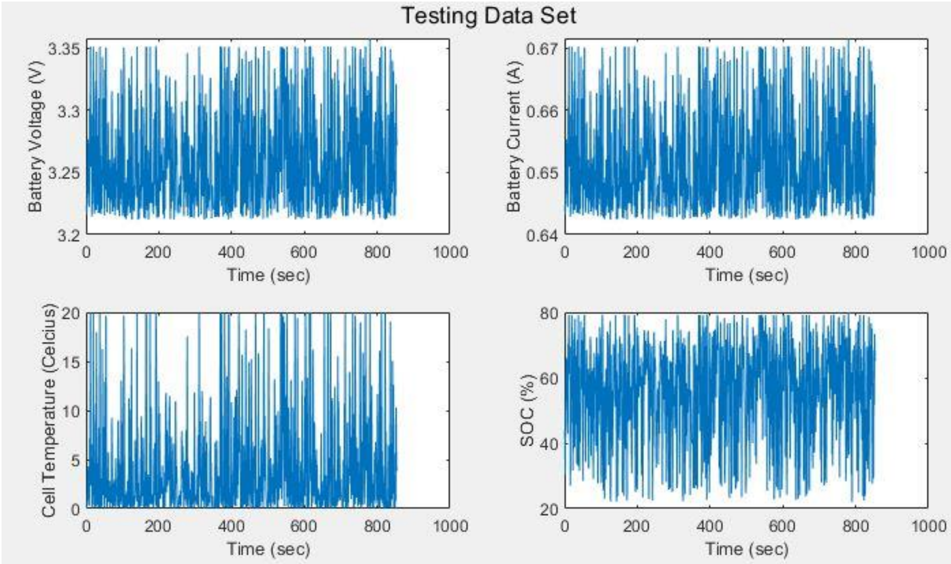


Fig.4.5: Testing Data Set (Discharging Operation)

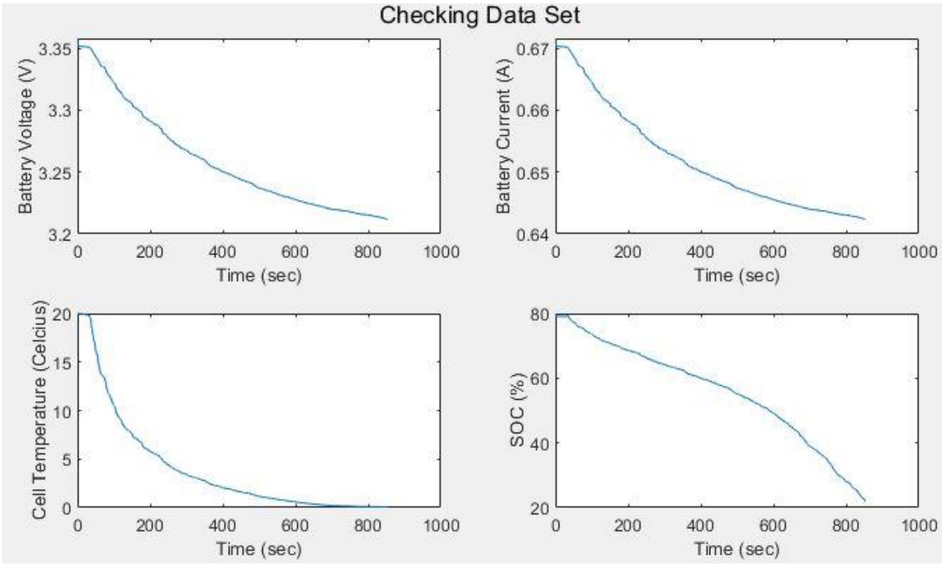


Fig.4.6: Checking Data Set (Discharging Operation)

Hybrid Electric Vehicle Operation

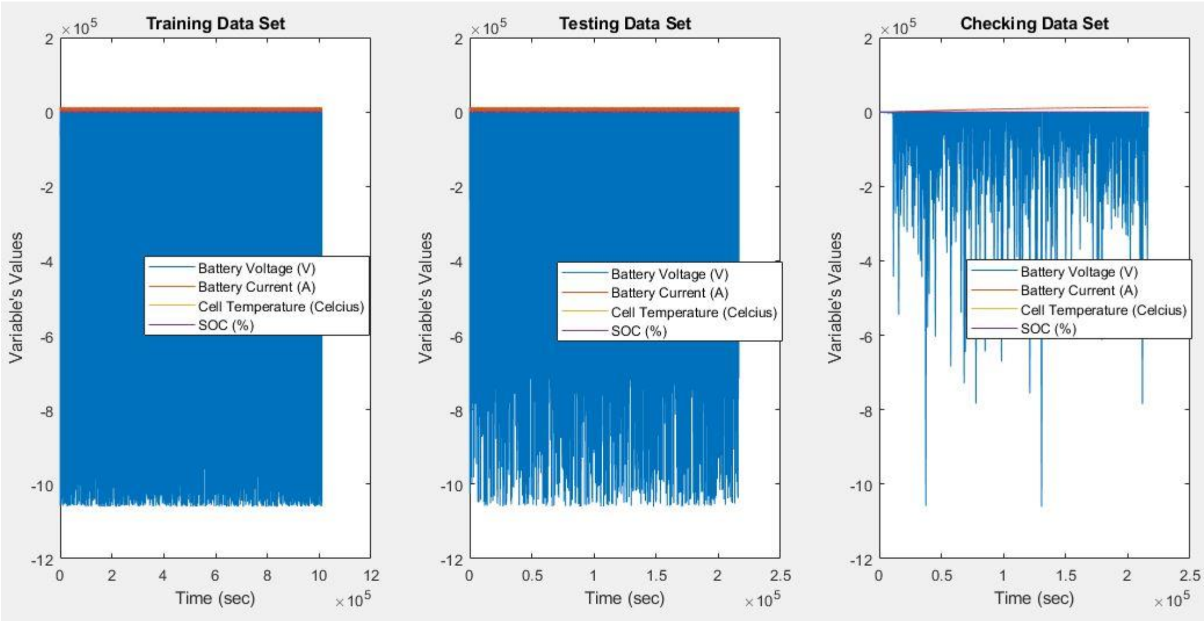


Fig.4.7: All Data Sets without zoom (Hybrid Electric Vehicle Operation)

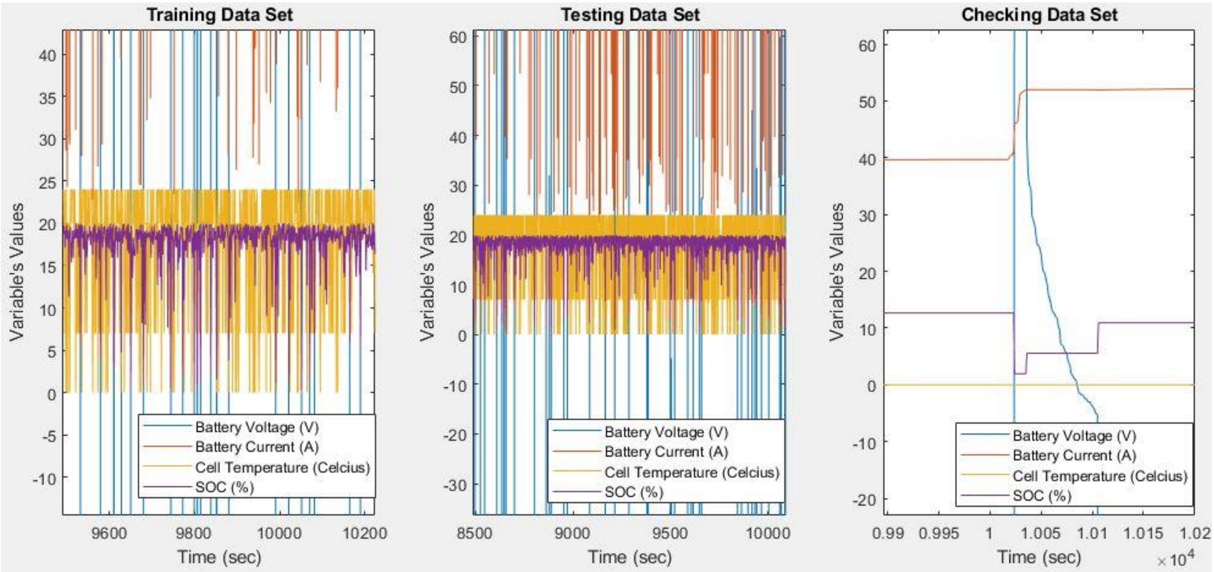


Fig.4.8: All Data Sets without zoom (Hybrid Electric Vehicle Operation)

4.2 Structure

As mentioned before, ANFIS is an adaptable and trainable network with a similar functionality to a fuzzy inference system. Generally, ANFIS performs the following steps:

- Receiving the training data
- Mapping the input characteristics to membership functions
- Applying specific rules on the input data from the previous step
- Define outputs based on the rules
- Mapping the output characteristics to output membership functions
- Calculating the total single valued output of the whole network

The structure of the proposed ANFIS is shown in Fig.4.9:

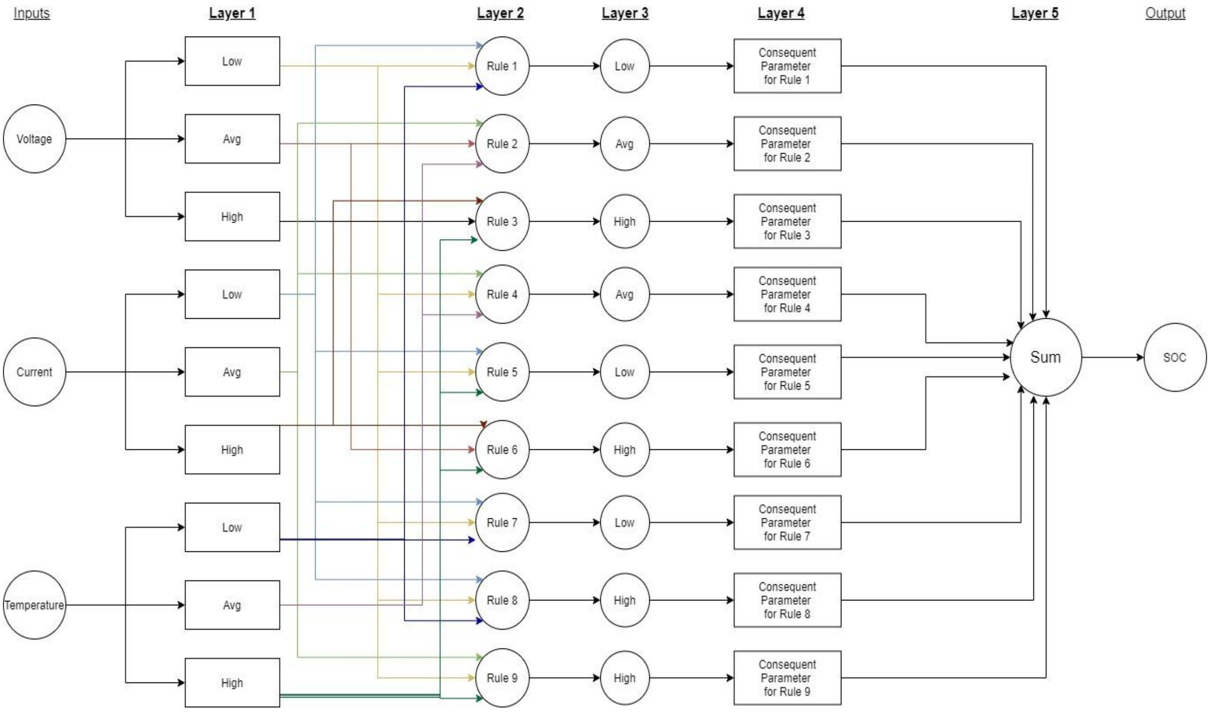


Fig.4.9: Proposed ANFIS

Layer 1

The first layer of the ANFIS or Fuzzification is the membership function layer of the input parameters. All the nodes in this layer are adaptive nodes. In the context of this thesis, the Gaussian membership function has been utilized, it is considered more suitable for three input parameter problems compared to Trapezoidal (four parameters) or Triangular (three or more).

$$\mu = \exp\left(-\left\{\left(\frac{x-c_i}{a_i}\right)^2\right\}^{b_i}\right) \quad i = 1, 2, 3$$

Where a_i, b_i and c_i are the so-called premised parameters.

The outputs of the first layer to be in the following form:

$$O_i^1 = \mu A_i(voltage) \quad \text{i = 1, 2, 3}$$
$$O_i^1 = \mu B_i(current) \quad \text{i = 1, 2, 3}$$
$$O_i^1 = \mu C_i(temperature) \quad \text{i = 1, 2, 3}$$

Where A, B, C are the nodes for voltage, current and temperature respectively, e.g. A_2 = average (avg), C_3 = high etc.

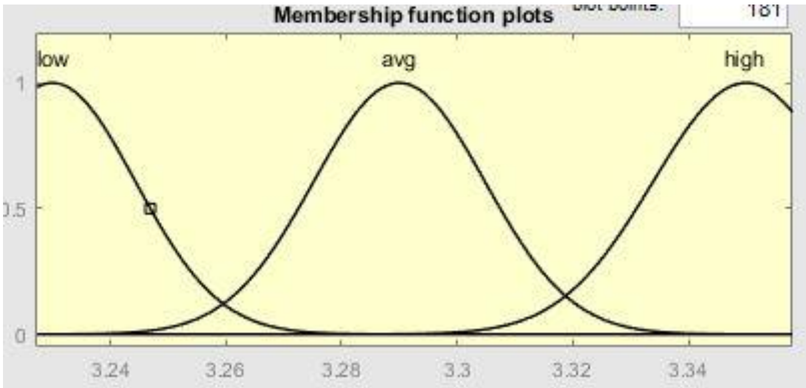


Fig.4.10: Gaussian membership function

Where y axis refers to the degree of the membership function and x axis refers to the crisp values (e.g. in Fig.4.10 variable voltage (V)).

Layer 2

The fuzzy rules inside the ANFIS define the output based on a specific value of the inputs and have a form of if-then rule:

- If (voltage is low) and (current is low) and (temperature is low) then (soc is low).
- If (voltage is avg) and (current is avg) and (temperature is avg) then (soc is avg).
- If (voltage is high) and (current is high) and (temperature is high) then (soc is high).
- If (voltage is low) and (current is avg) and (temperature is avg) then (soc is avg).
- If (voltage is low) and (current is low) and (temperature is high) then (soc is low).
- If (voltage is avg) and (current is high) and (temperature is high) then (soc is high).
- If (voltage is not low) and (current is low) and (temperature is low) then (soc is low).
- If (voltage is not low) and (current is not low) and (temperature is not low) then (soc is high).
- If (voltage is not low) and (current is not avg) and (temperature is not high) then (soc is high).

The above fuzzy rules summarize all the possible input combinations as shown in Table.4.1

INPUTS			**OUTPUT**
Voltage	**Current**	**Temperature**	**SOC**
low	low	low	low
low	low	avg	low
low	low	high	avg
low	avg	low	low
low	avg	avg	low
low	avg	high	high
low	high	low	avg
low	high	avg	high
low	high	high	high
avg	low	low	low
avg	low	avg	avg
avg	low	high	high
avg	avg	low	avg
avg	avg	avg	avg
avg	avg	high	high
avg	high	low	high
avg	high	avg	high
avg	high	high	high
high	low	low	low
high	low	avg	avg
high	low	high	high
high	avg	low	avg
high	avg	avg	avg
high	avg	high	high
high	high	low	high

high	high	avg	high
high	high	high	high

Table.4.1:All possible input combinations

The output of the second layer is the multiplication of input signals, which is actually equivalent to the "if" part of the rules. In this layer, the weights of each rule will be computed through a fuzzy AND operation. The nodes in this layer are all fixed nodes. The following equation presents the output of this layer:

$$O_i^2 = w_i = \mu A_i(voltage) * \mu B_i(current) * \mu C_i(temperature) \quad \text{i = 1, 2, 3}$$

Layer 3

The third layer normalizes the values from the previous layer. The output of this layer can be shown by:

$$O_i^3 = W_i = \frac{w_i}{w_1+w_2+w_3} \text{ i =1, 2, 3}$$

Layer 4

The Defuzzification process takes place in the fourth layer. All the nodes in this layer are also adaptive nodes. The outputs of these nodes are the product of Layer 3 and the individual rule output of associated rule, which is actually equivalent to the "then" part of the rules. The corresponding output formula for this layer can be expressed as:

$$O_i^4 = O_i^3 * f_i(soc) = W_i * (p_i * voltage + q_i * current + r_i * temperature + s_i) \text{ i=1, 2, 3}$$

Where p, q, r and s are so-called consequent parameters

Layer 5

The final layer presents the overall output of the whole network and it contains a single fixed node which sums up the results from the previous layer:

$$O_i^5 = \sum_{i=1}^{3} O_i^4$$

4.3 Training Method

There are two main steps in the pipeline based on the ANFIS model. The first step is training, in which the membership function parameters are modified, so that the desired patterns and relations between the inputs and outputs are learned by the system. The training data batches will be presented to the network many times (iterations) until the desired results are obtained. In most cases the root mean square error is used between output and target value. The next step is testing the trained network with the rest of the data.

So, the most important part of the ANFIS network is the fuzzy inference system which tries to learn the algorithm or any possible relationship between input/output and adjust the premise and consequent parameters so that the final outputs of the ANFIS match the training results.

When the premise parameters are not stable, the convergence speed will be slower, since the search area is larger. A hybrid algorithm of least square method and gradient descent, which were discussed in part 2.1.3.2, has shown great potential in overcoming this problem. This algorithm performs a forward delivery process and then a back propagation process. When the premise parameters are determined, the least square method will be applied to optimize the consequent parameters. After calculating the best consequent parameters, the back propagation process will start and the gradient descent process will adjust the premise parameters based on the fuzzy sets in the entry field. In other words, the ANFIS network calculates the consequent parameters in the feed forward process and the premise parameters will be modified by back propagation algorithm according to the output error. This hybrid approach has shown the best results and highest efficiency in training the neuro-fuzzy networks and it has been applied in the model developed in this thesis.

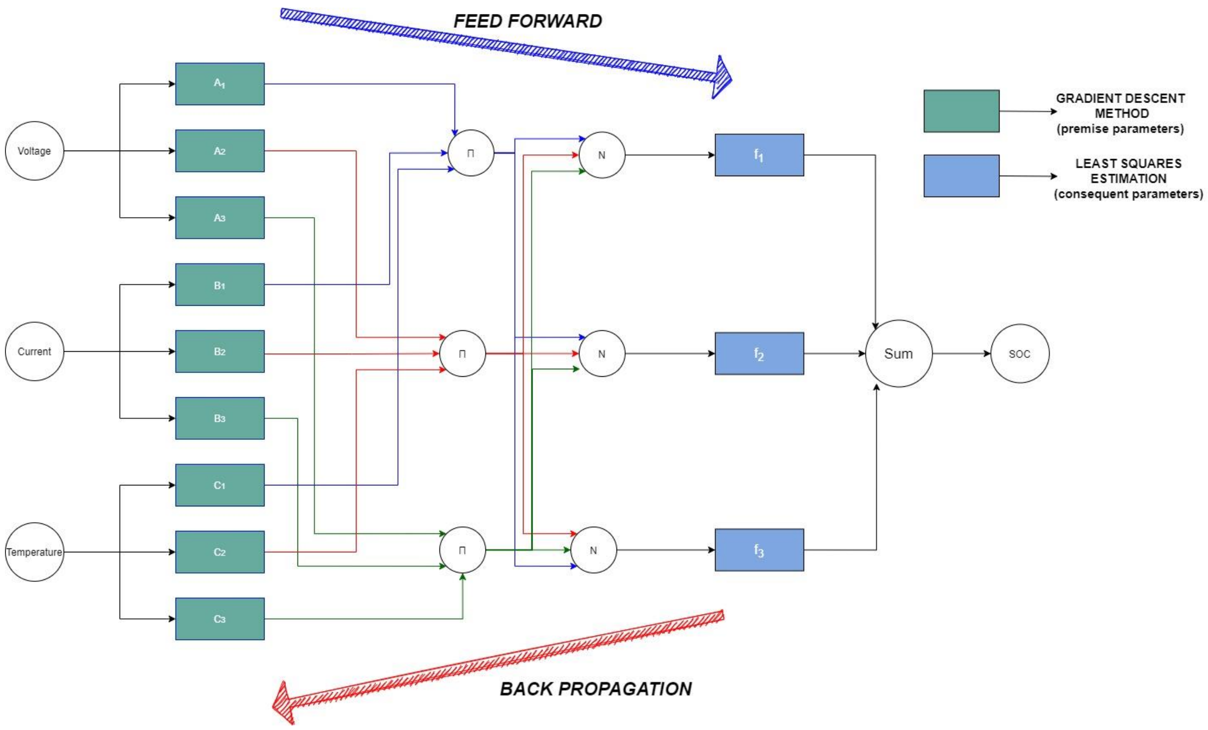


Fig.4.11: Schematic of hybrid approach

4.4 Implementation

Next, the ANFIS model in Matlab was provided with the simulated data mentioned above. Firstly, by the command ‘anfisedit’ the aforementioned data file were imported into ANFIS. Voltage, Current and Temperature were used as inputs and SOC as the singular output.

Charging Operation

For the charging operation mode, the data set included 65591 samples. From those, the 45917 were used as the training data set, while the checking and testing data constituted of 9838 data-points each (as shown in Fig.4.12). Next, the FIS system was generated as discussed in Section 4.2 (the same system was used for discharging and hybrid electric vehicle operation). Afterwards, the ANFIS was trained using 10 epochs and zero error tolerance. The hybrid optimization method was used. The result can be seen in Fig.4.13.

```
ANFIS info:
    Number of nodes: 42
    Number of linear parameters: 36
    Number of nonlinear parameters: 18
    Total number of parameters: 54
    Number of training data pairs: 45914
    Number of checking data pairs: 9838
    Number of fuzzy rules: 9
```

Fig.4.12: ANFIS info extracted from Matlab

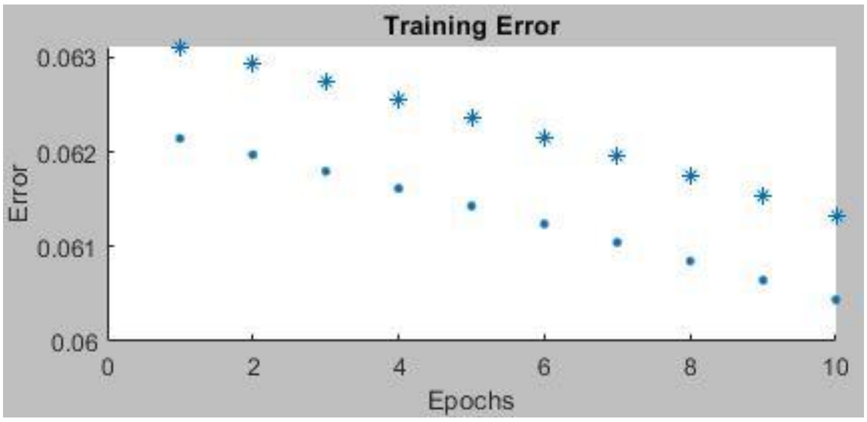


Fig.4.13: Training error of charging operation

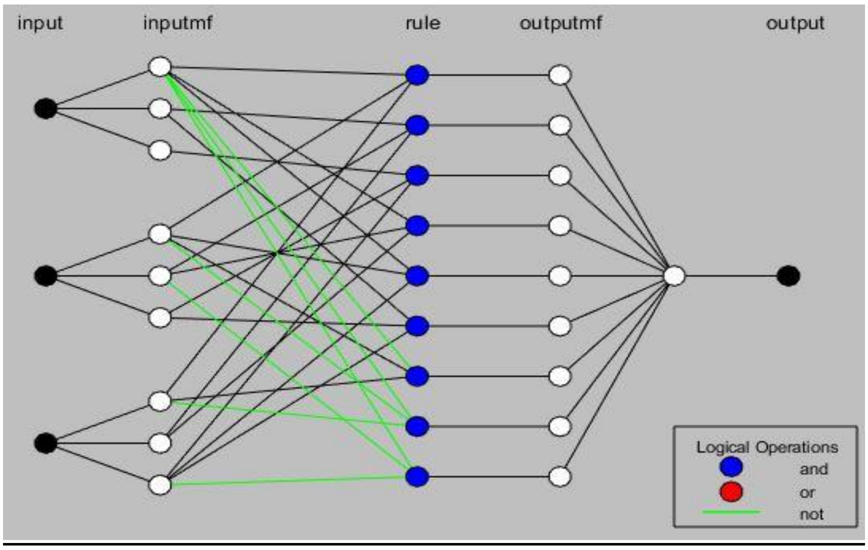


Fig.4.14: ANFIS Charging Operation Structure

Following, the testing process evaluated the testing error based on the checking data as is illustrated in Fig.4.15

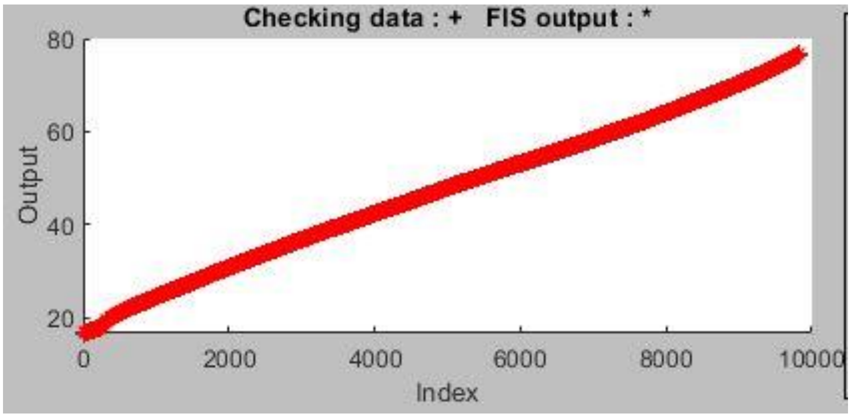


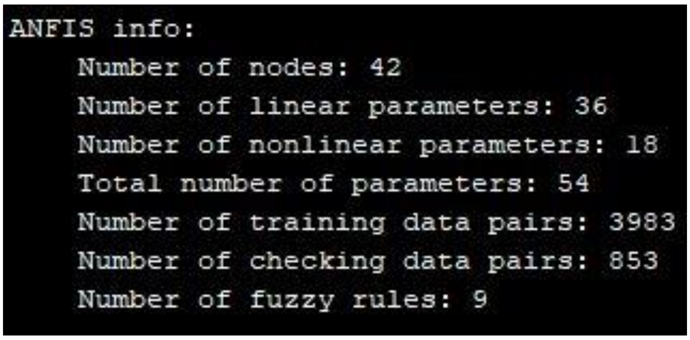
Fig.4.15: Testing of charging operation

Where the label 'Output', in y axis, refers to the SOC (%) and the label 'Index', in x axis, refers to the time (sec).

The same procedure was followed for the discharging and the hybrid electric vehicle operations.

Discharging Operation

For the discharging operation mode, the data set included 5690 samples. From those, the 3983 were used in the training data set, while the checking and testing data consisted of 853 data-points each (as shown in Fig.4.16).



```
ANFIS info:
    Number of nodes: 42
    Number of linear parameters: 36
    Number of nonlinear parameters: 18
    Total number of parameters: 54
    Number of training data pairs: 3983
    Number of checking data pairs: 853
    Number of fuzzy rules: 9
```

Fig.4.16: ANFIS info extracted from Matlab

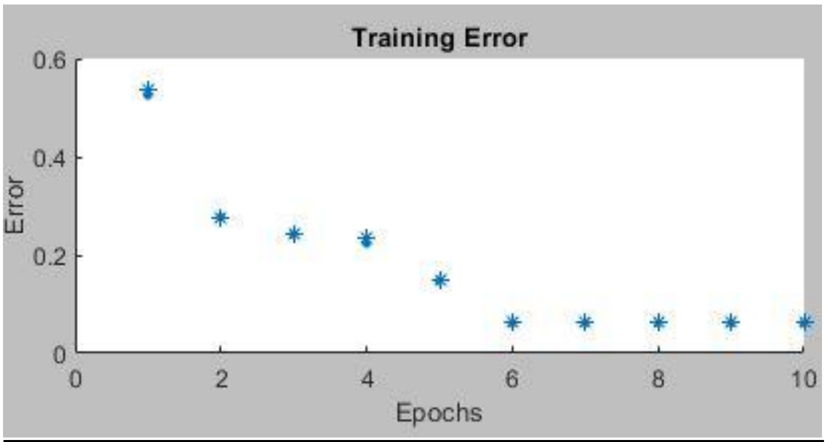


Fig.4.17: Training error of discharging operation

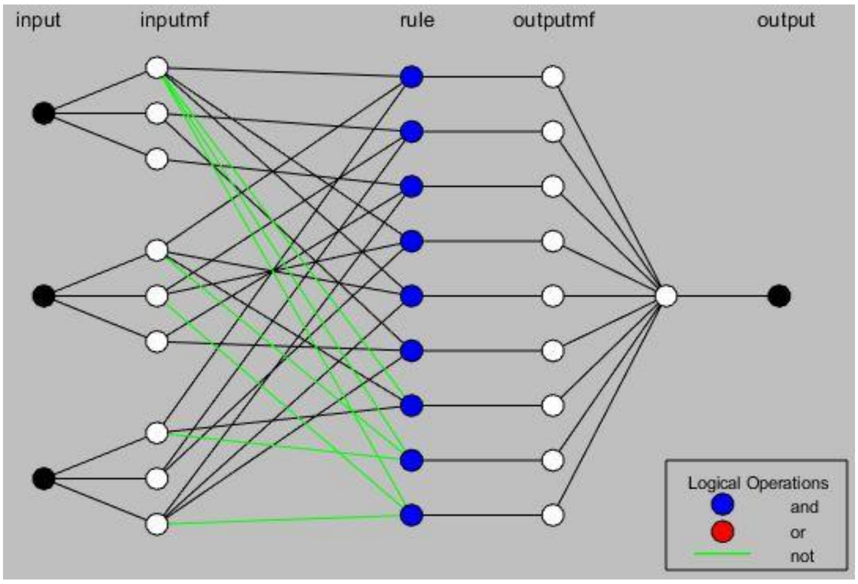


Fig.4.18: ANFIS Discharging Operation Structure

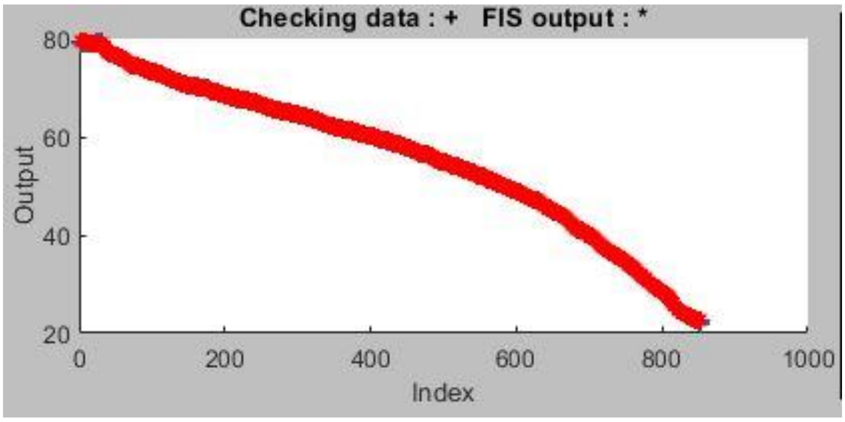


Fig.4.19: Testing of discharging operation

Where the label ‘Output’, in y axis, refers to the SOC (%) and the label ‘Index’, in x axis, refers to the time (sec).

Hybrid Electric Vehicle Operation

For the hybrid electric vehicle operation mode, the file included 216538 data points. From those, 1010509 were used as the training data set, while the checking and testing data were 216538 each (as shown in Fig.4.20).

```
ANFIS info:
    Number of nodes: 42
    Number of linear parameters: 36
    Number of nonlinear parameters: 18
    Total number of parameters: 54
    Number of training data pairs: 1010509
    Number of checking data pairs: 216538
    Number of fuzzy rules: 9
```

Fig.4.20: ANFIS info extracted from Matlab

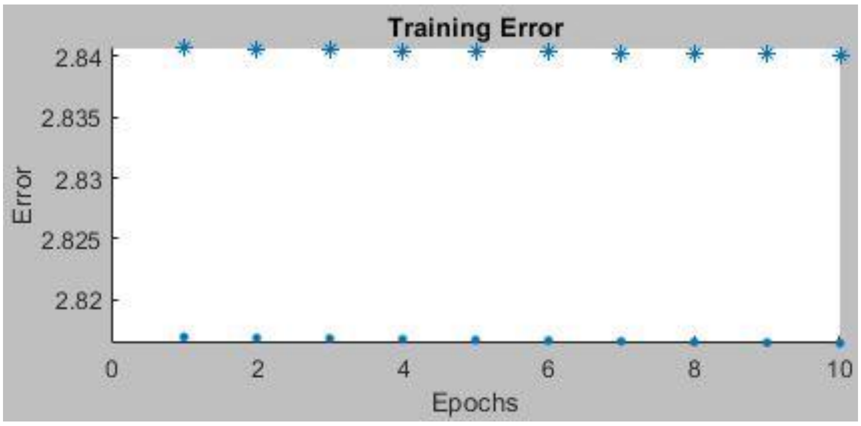


Fig.4.21: Training error of hybrid electric vehicle operation

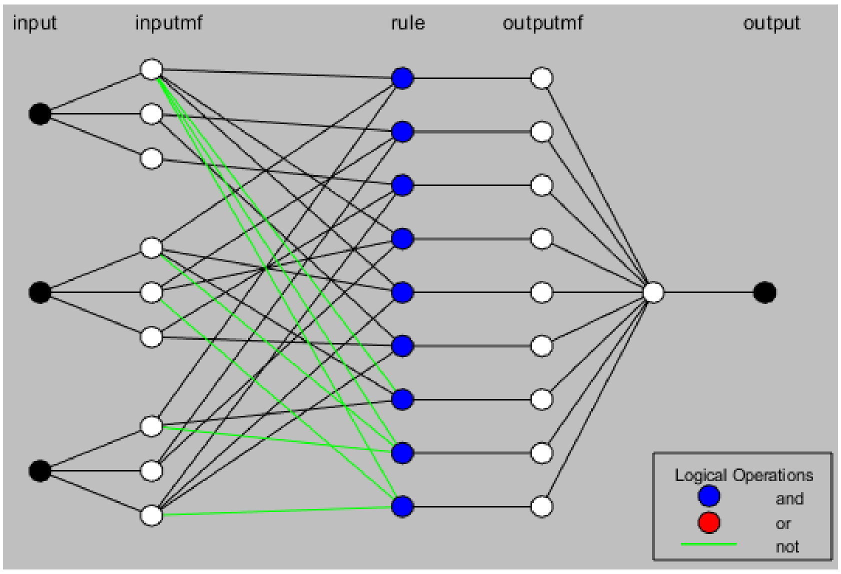


Fig.4.22:ANFIS Hybrid Electric Vehicle Operation Structure

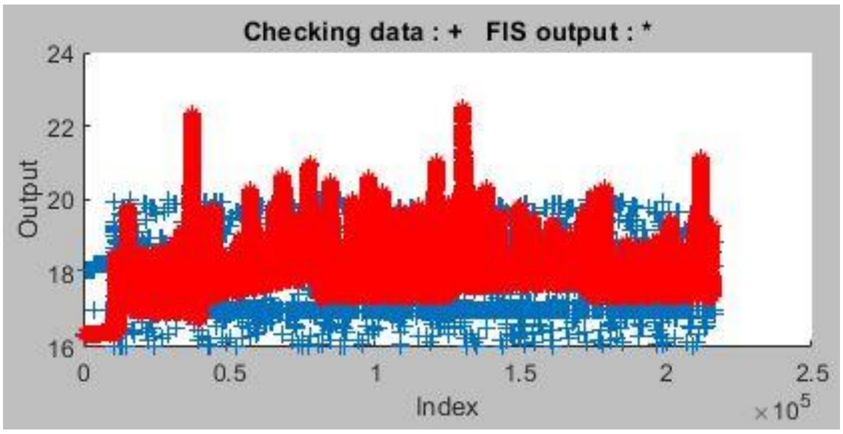


Fig.4.23: Testing of hybrid electric vehicle operation

Where the label 'Output', in y axis, refers to the SOC (%) and the label 'Index', in x axis, refers to the time (sec).

4.5 Results

The accuracy of SOC estimation is a crucial part of using Lithium-Ion batteries in energy storage or hybrid electric vehicles in order to reduce the depreciation and also increase the cycle of the batteries.

The output of the proposed model based on ANFIS show very accurate and efficient results. The root mean square error (RMSE) for each epoch and the average testing error for each system are the following:

Epoch	Minimal Training RMSE	Minimal Checking RMSE
1	0.062934	0.0619728
2	0.062746	0.0617968
3	0.062555	0.061616
4	0.062359	0.0614305
5	0.062159	0.0612404
6	0.061954	0.061046
7	0.061747	0.0608474
8	0.061536	0.0606449
9	0.061321	0.0604389
10	0.061105	0.0602297

Table.4.2: Errors for epoch 1 to 10 during ANFIS training model for Charging Operation

Average Testing Error	0.06359

Table.4.3: Average Testing Error during ANFIS training model for Charging Operation

Epoch	Minimal Training RMSE	Minimal Checking RMSE
1	0.274560	0.27727
2	0.242231	0.241882
3	0.232937	0.223535
4	0.147370	0.147752
5	0.061645	0.0614042
6	0.061645	0.0614042
7	0.061644	0.0614041
8	0.061644	0.0614041
9	0.061642	0.0614039
10	0.061642	0.0614039

Table.4.4: Errors for epoch 1 to 10 during ANFIS training model for Discharging Operation

Average Testing Error	0.0611404

Table.4.5: Average Testing Error during ANFIS training model for Discharging Operation

Epoch	Minimal Training RMSE	Minimal Checking RMSE
1	2.840568	2.81687
2	2.840505	2.81681
3	2.840445	2.81675
4	2.840385	2.8167
5	2.840327	2.81664
6	2.840270	2.81658
7	2.840214	2.81653
8	2.840158	2.81647
9	2.840104	2.81642
10	2.840051	2.81637

Table.4.6: Errors for epoch 1 to 10 during ANFIS training model
for Hybrid Electric Vehicle Operation

Average Testing Error	2.8164

Table.4.7: Average Testing Error during ANFIS training model
for Hybrid Electric Vehicle Operation

The results presented in the previous tables and illustrated from Fig.4.2 to Fig.4.7, show that the proposed ANFIS system can easily be used during charging, discharging operations as well as for a hybrid electric vehicle battery. For a variety of different data sets the error ranged from 0.061 to 0.064 for the charging system, from 0.275 to 0.061 for discharging operations and from 2.81 to 2.85 for hybrid electric vehicle operation. In addition, the proposed algorithm has an average of milliseconds runtime for charging and discharging system and seconds (sometimes up to a minute) for hybrid electric vehicle.

4.6 Results MyAnfis application and comparison with the proposed ANFIS

Charging Operation

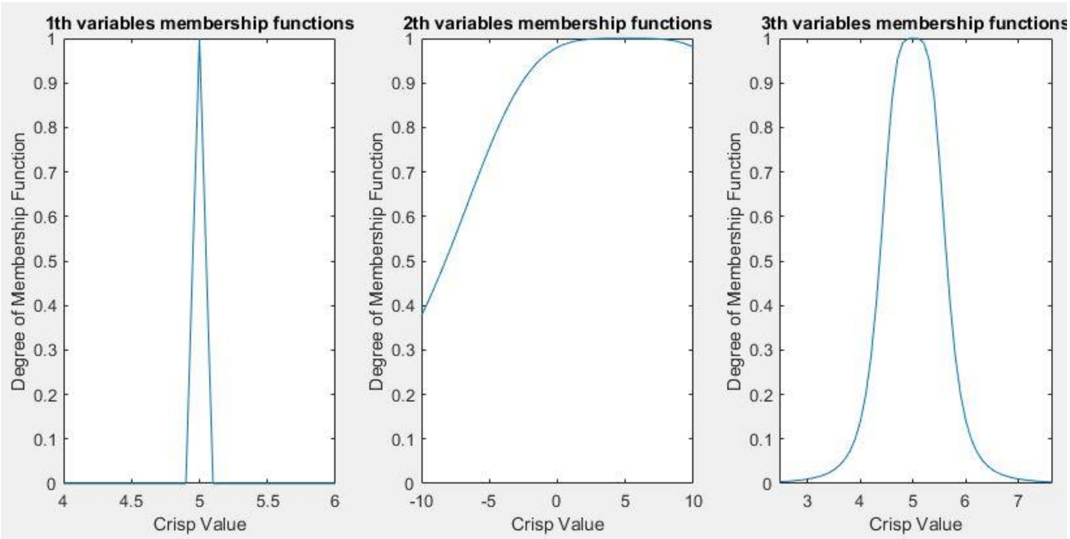


Fig.4.24: Membership functions of Charging Operation (MyAnfis)

Where the "Crisp Value" is each input of MyAnfis. For the "1th variable membership functions" the crisp value is the voltage, for the second the current and for the third the cell temperature.

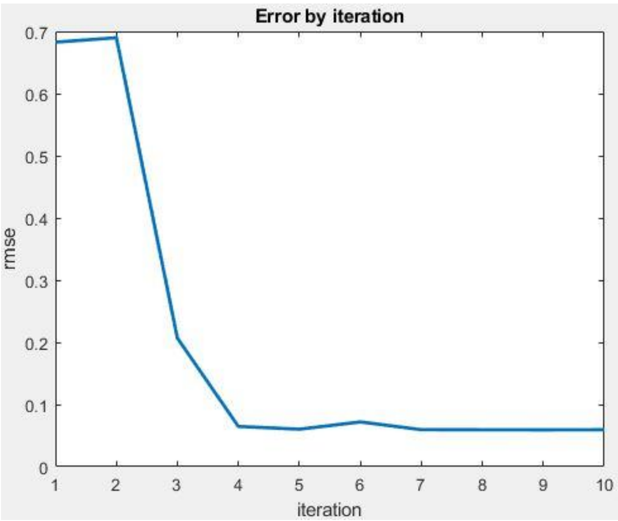


Fig.4.25: RMSE of Charging Operation (MyAnfis)

```
1. rmse error : 0.682669
2. rmse error : 0.689882
3. rmse error : 0.206944
4. rmse error : 0.0647888
5. rmse error : 0.0602767
6. rmse error : 0.0719973
7. rmse error : 0.0595165
8. rmse error : 0.0593895
9. rmse error : 0.0591815
10. rmse error : 0.059454
```

Fig.4.26: RMSE per epoch of Charging Operation (MyAnfis)

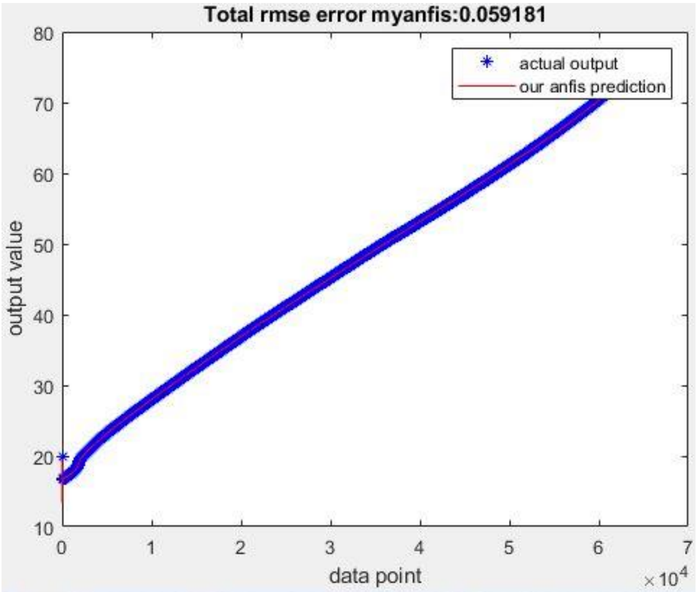


Fig.4.27: Total Error of Charging Operation (MyAnfis)

Where the label ‘output value’, in y axis, refers to the SOC (%) and the label ‘data point’, in x axis, refers to the time (sec).

MyAnfis implementation has a better average RMSE (0.059181) than the proposed ANFIS (0.06359). On the other hand, MyAnfis’ runtime was 10 minutes in comparison with the proposed technique, which needed an average of milliseconds.

Discharging Operation

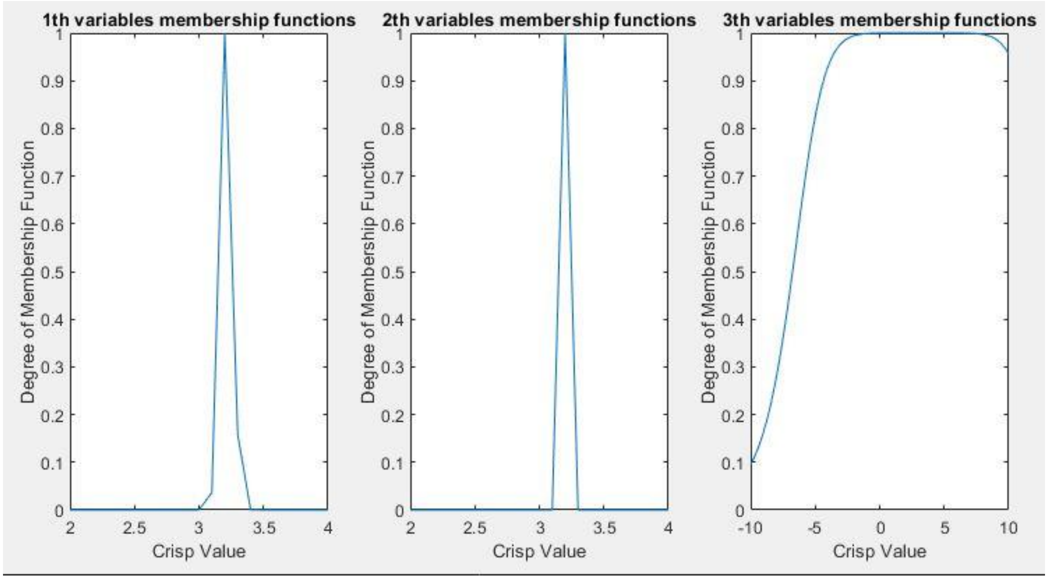


Fig.4.28: Membership functions of Discharging Operation (MyAnfis)

Where the "Crisp Value" is each input of MyAnfis. For the "1th variable membership functions" the crisp value is the voltage, for the second the current and for the third the cell temperature.

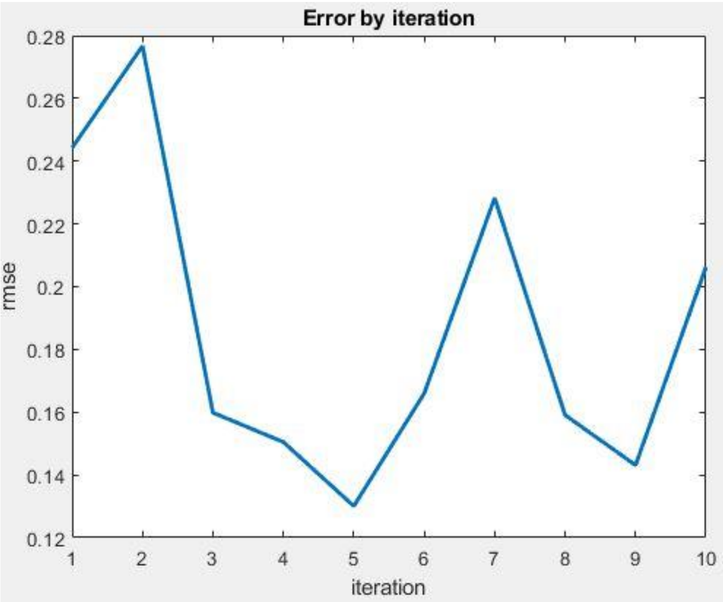
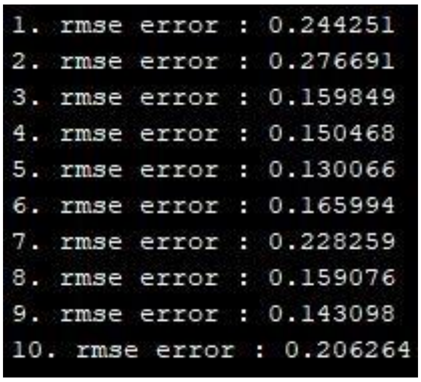


Fig.4.29: RMSE of Discharging Operation (MyAnfis)



```
1. rmse error : 0.244251
2. rmse error : 0.276691
3. rmse error : 0.159849
4. rmse error : 0.150468
5. rmse error : 0.130066
6. rmse error : 0.165994
7. rmse error : 0.228259
8. rmse error : 0.159076
9. rmse error : 0.143098
10. rmse error : 0.206264
```

Fig.4.30: RMSE per epoch of Discharging Operation (MyAnfis)

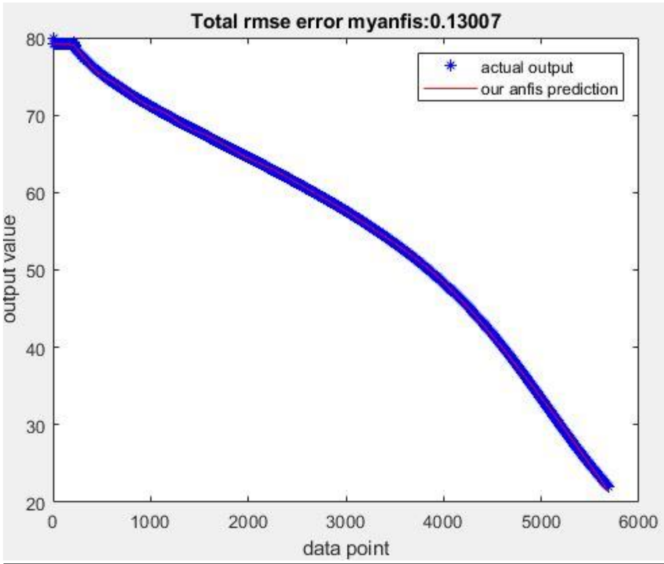


Fig.4.31: Total Error of Discharging Operation (MyAnfis)

Where the label ‘output value’, in y axis, refers to the SOC (%) and the label ‘data point’, in x axis refers to the time (sec).

The proposed ANFIS has a better average RMSE (0.0611404) than the MyAnfis implementation (0.13007). Moreover, MyAnfis’ estimated runtime was 10 minutes in comparison with the proposed technique, which needed an average of milliseconds.

Hybrid Electric Vehicle Operation

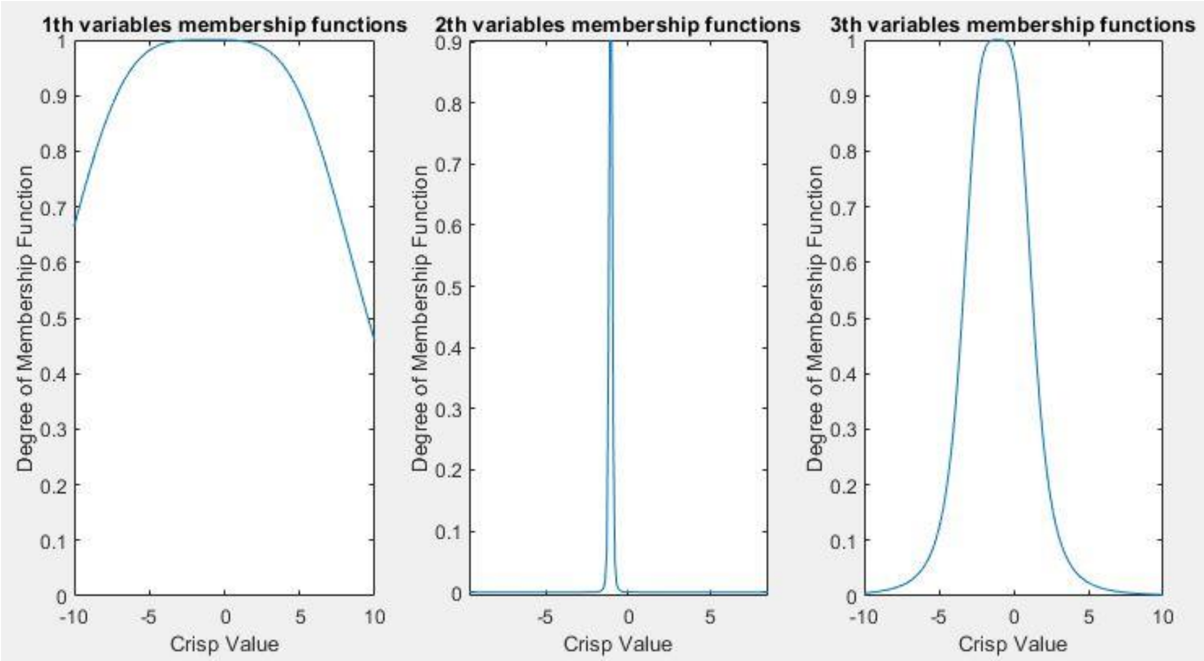


Fig.4.32: Membership functions of Hybrid Electric Vehicle Operation (MyAnfis)

Where the “Crisp Value” is each input of MyAnfis. For the “1th variable membership functions” the crisp value is the voltage, for the second the current and for the third the cell temperature.

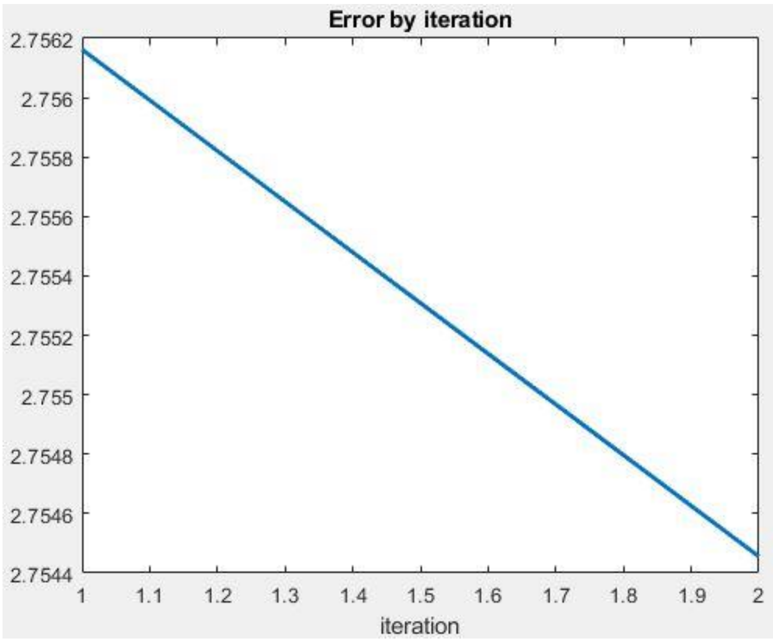
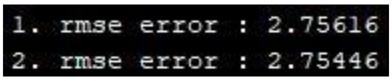


Fig.4.33: RMSE of Hybrid Electric Vehicle Operation (MyAnfis)



```
1. rmse error : 2.75616
2. rmse error : 2.75446
```

Fig.4.34: RMSE per epoch of Hybrid Electric Vehicle Operation (MyAnfis)

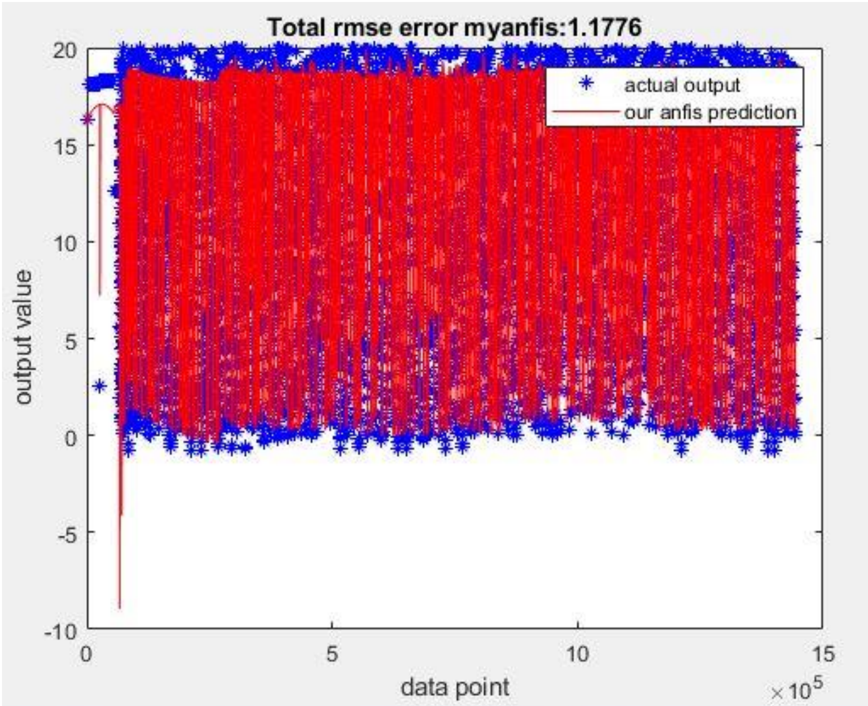


Fig.4.35: Total Error of Hybrid Electric Vehicle Operation (MyAnfis)

Where the label ‘output value’, in y axis, refers to the SOC (%) and the label ‘data point’, in x axis, refers to the time (sec).

MyAnfis implementation has a better average RMSE (1.1776) than the proposed ANFIS (2.8164). On the other hand, MyAnfis’ estimated runtime was 6 hours in comparison with the proposed technique, which needed some minutes.

CHAPTER 5: CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

The rapid development in hybrid electric vehicles and systems working isolated from the grid, make energy storage systems a key element, with batteries being one of the most popular. Although battery systems are widely studied, the vast majority of researches are focused on electrochemical static models and low frequency internal impedance analysis. An important part of this work was to implement an algorithm that can be used in both charging, discharging operation modes of a battery as well as in the single battery of a hybrid electric vehicle operation.

Lithium model battery for (dis)charging a hybrid electric vehicle was simulated for the effects of temperature on its performance. Motivated by the requirements of safe, reliable, and efficient utilization of lithium-ion batteries, this thesis developed a technique for battery states of charge estimation, which are capable of determining internal battery status accurately. The Adaptive Neuro Fuzzy Inference System is a classic example of such an approach, where the number of fuzzy rules is related to the number of input variables as well as the number of membership functions for each input.

The proposed model was developed in Matlab/Simulink in order to predict the state of charge of the battery. The results were significantly lower than most reported cases in similar studies. Moreover, the proposed ANFIS has similar error values, but faster runtime than the MyAnfis model. To summarize, the proposed method offers a more efficient, time-saving and more accurate approach, especially in charging and discharging operation of the battery.

5.2 Future Work

This project constitutes a proof of concept that an adaptive neuro fuzzy inference system is able to accurately estimate the SOC in energy storage systems such as batteries. In this thesis, an algorithm for a lithium-ion battery has been developed. The aim of future researches is to study if the algorithm can be developed in an integrated battery pack system as well as what changes have to be done in order to achieve this. The changes may be in the fuzzy inference model and especially in membership functions, the rules or the number of inputs. Other future work could develop an extension of the proposed ANFIS model for hybrid electric vehicles with high energy storage needs.

APPENDIX

A. MyAnfis Implementation

First of all, the number of epoch (epoch_n) and of membership functions (mf), the step size and decrease/increase rate were defined.

epoch_n=10;
mf=2;
step_size=0.1;
decrease_rate=0.9;
increase_rate=1.1;

After that, the input data were inserted. Then the MyAnfis algorithm was implemented as shown in Fig.A.1 [43].

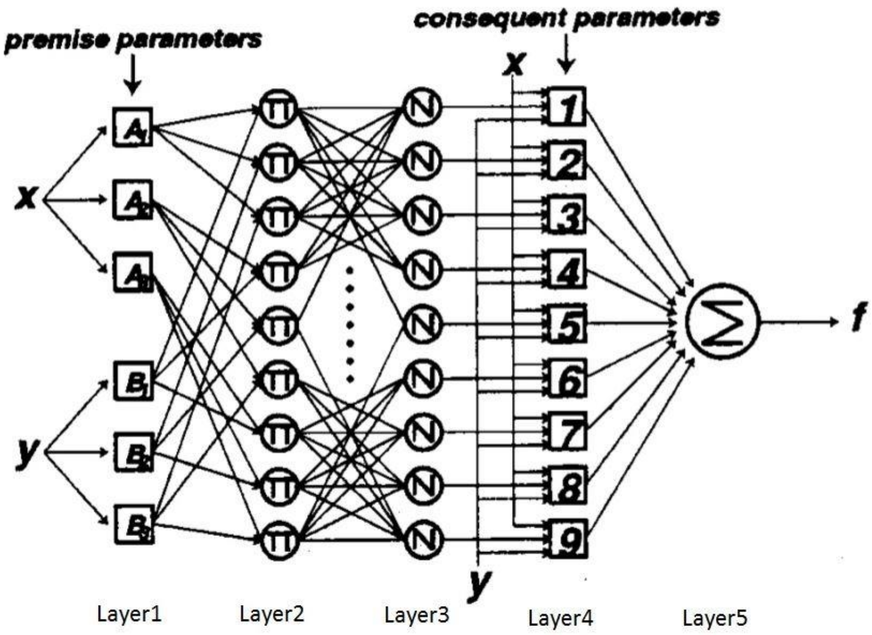


Fig.A.1: Structure of MyAnfis

The structure is similar to the proposed ANFIS (Section 4.2), but with two differences. Firstly, MyAnfis use Kalman Filtering in order to tune the consequent parameters. Kalman filtering gives the probability that each x, y (Layer 4 in Fig.A.1) falls in a particular range of discrete set of values, that was set by the linguistic labels (A, B), using joint probability distribution. Another difference is the membership function. On the MyAnfis the generalized bell function is used:

$$\mu_{Ai}(x) = \frac{1}{1+ [(\frac{x-c_i}{a_i})^2]^{b_i}} \quad i = 1, 2$$

Where { a_i, b_i, c_i } are the premise parameters of the generalized bell function. As the values of these parameters change, the membership function varies accordingly [see Fig.A.2] [44].

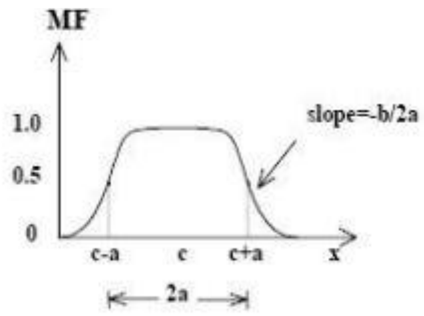


Fig.A.2: Generalized bell function with the premise parameters

The premise parameters for the charging operation mode are:

	1	2	3
1	1.4803e-16	2	5
2	1.4803e-16	2	5.0000
3	13.2314	2	5
4	13.2314	2	5.0000
5	0.6357	2	5
6	0.6357	2	5.0000

Table.A.1: Premise Parameters of Charging Operation (MyAnfis)

The first column is the ‘a’ premise parameter, the second column is ‘b’ and the third is ‘c’. Each column represents the membership function of each input variable of MyAnfis model. For example, the first two rows (mf=2) are the membership functions of the input variable voltage.

The premise parameters for the discharging operation mode are:

	1	2	3
1	0.0731	4	3.2100
2	0.0731	4	3.3500
3	0.0292	4	3.2100
4	0.0292	4	3.3500
5	9.9609	4	3.2100
6	9.9609	4	3.3500

Table.A.2: Premise Parameters of Charging Operation (MyAnfis)

The first column is the ‘a’ premise parameter, the second column is ‘b’ and the third is ‘c’. Each column represents the membership function of each input variable of MyAnfis model.

For example, the third and fourth rows (mf=2) are the membership functions of the input variable current.

The premise parameters for the hybrid electric vehicle operation mode are:

	1	2	3
1	10.6100	2	-1.0605
2	10.6100	2	545.3376
3	0.1235	2	-1.0605
4	0.1235	2	545.3376
5	2.4000	2	-1.0605
6	2.4000	2	545.3376

Table.A.2: Premise Parameters of HEV Operation (MyAnfis)

The first column is the ‘a’ premise parameter, the second column is ‘b’ and the third is ‘c’. Each column represents the membership function of each input variable of MyAnfis model.

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