ADVANCES IN BATTERY MANAGEMENT USING NEURAL NETWORKS AND FUZZY LOGIC

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ABSTRACT

Conventional methods of battery management, which deals with regulating the charging, protection and monitoring of the battery, are inefficient for two reasons. First, they do not adapt to the battery in question and second, they require the battery to be "off-line" for the duration of the measurements of the battery parameters. New battery models improve by combining elements of conventional static battery management techniques with adaptive, dynamic elements drawn from neural networks and fuzzy logic theory. Such use of neural networks and fuzzy logic reduces the need for empirically derived constants, offering dynamic solutions for battery management. In this paper I identify the research on battery management using neural networks, fuzzy logic and neuro-fuzzy systems. The algorithms used for estimation of state of charge or state of health are compared by the error rates achieved. Weaknesses in the present research and areas for improvement are identified to present an overview of the battery techniques that have been used successfully in industry and in academia.

1 Introduction

The last decade has seen the development of mobile devices such as laptops and cellphones. Better power management, allowing for longer periods of usage without recharging, has been at the heart of this transition towards more portable solutions [1]. While the most easily evident of these changes has been in the internal chemistry of the batteries, a revolution has been occurring in the field of battery management which deals with regulating the charging, protection and monitoring of the battery [2]. The emergence of embedded and distributed computing has opened the window for a new generation of solutions that harness the power of embedded systems dedicated for battery management [3]. In these more accurate models, elements of conventional static battery management techniques are combined with adaptive, dynamic elements drawn from neural network and fuzzy logic theory. [4].

Battery management system (BMS) refers to software and hardware designed to maximize each discharge cycle of a battery while maximizing the lifetime of the battery [1]. There are two variables that summarize the BMS for our purposes. The first, State of Charge (SOC) refers to the amount of charge present in a battery in a charge or discharge cycle. The second, State of Health (SOH) represents the performance of the battery compared to its past and expected future.

Neither the SOC nor the SOH is directly measurable and needs to be inferred from other measurements. There are four methods for assessing the SOC and SOH of a battery. The first class of methods involves making appraisals of the battery components, such as measuring the specific gravity of the electrolyte. The second class of methods uses parameters of the battery that can be measured directly, such as the terminal voltage and the internal impedance of the battery [5]. The measurements of the terminal voltage, the voltage present when the battery is in open circuit, are used to predict the SOC as in Figure 1 where a relationship can be seen between the terminal voltage and the SOC [6]. The third class of methods involves using the Peukert's equation for battery capacity, or a derivative of this equation, which relates the capacity of the battery to the current and the temperature. This equation, with the constants measured by testing batteries in laboratories, is used to model the battery and measurements of the current are fed into the equation to get the remaining battery capacity [6]. The fourth class of methods uses a measurement of the charge being transferred across the battery to infer SOC and SOH and control the charging and discharging of the battery [7, 8].

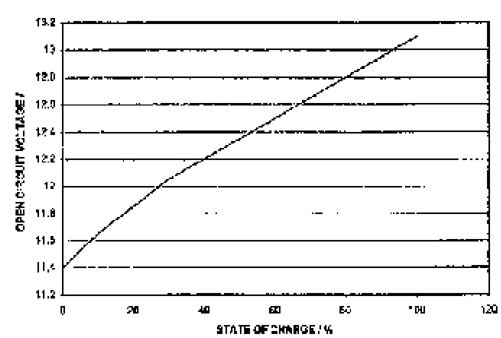

Figure 1: Sample relationship between terminal voltage and SOC [6]

These conventional methods of battery management are inefficient for two reasons. The first limitation involves having to use values of "baseline" models that represent the average of the results seen in the laboratory. For real-life situations where batteries show a large variation in their properties, the accuracy of the conventional models is limited [9]. Furthermore, as a battery ages the properties of the battery change, increasing the inefficiencies of the modeling. The second limitation involves having to measure the parameters of the battery, be it either the terminal voltage or the internal impedance, with the battery “offline”, or out of service, for the duration of the measurements [10].

The significance of SOC and SOH for the BMS is not limited to the accuracy of its predictions. A BMS, apart from exporting information about the battery, also has responsibilities towards protecting the battery [1]. The SOC and the SOH control the regulation of the battery, and especially in the case of Li-ion batteries, are hence responsible for preventing overcharge conditions that might cause the battery to explode [11]. A BMS is usually designed to regulate the discharging and charging current of a battery. The most common method of charge regulation is the voltage temperature cutoff (VTCO) charger [12]. In this charger the voltage and the temperature are used to determine the charge left in the battery and hence the rate of charging/discharging of the battery. Any errors in this estimation of SOC would affect regulation of the charge/discharge current and thus lead to a reduced battery capacity. Conversely, an increased accuracy in estimating the SOC and SOH increases the life and efficiency of the battery [13].

An answer lies in the use of neural networks and fuzzy logic. The use of neural networks and fuzzy logic, either separately or in combination, reduces the need for empirically derived constants. Instead of static solutions, neural networks and fuzzy logic offer dynamic solutions that address the stated problems with battery management [14, 15]. Furthermore, often the provided solutions can be extended to rely upon parameters that don’t require the battery to be taken offline.

Neural networks and fuzzy logic are mathematical models concerned with processing information in distributed nodes. A neural network is by nature adaptive and is able to process information that is relative while adapting to changing environments. Fuzzy logic, based upon fuzzy sets, is designed to model systems where there are relative factors that have changing levels of importance. Using these systems with the empirical models of batteries, allows us to endow the BMS with different adaptive and relative capabilities.

In this project I investigate solutions for battery management systems, focusing on those that use neural networks and fuzzy logic. The work of the different research teams is presented in separate summaries that focus on the types of algorithms used by the teams, the batteries that were tested on during the course of the research and the performance of the new SOC/SOH estimators vis-à-vis the performance of the conventional SOC/SOH estimators. Finally, conclusions are drawn based on these observations with an attempt to draw out the expected trends for further research.

2 METHODS

Research for this project was carried out using three major electronic gateways: Institute of Electrical and Electronic Engineers Xplorer, CiteSeer, and the gateway to the *Journal of Power Sources*. The section of battery management was drawn in part from the *Rechargeable Batteries Application Handbook* [12]. Information on neural networks and fuzzy logic was found in *Understanding Neural Networks and Fuzzy Logic: Basic Concepts and Applications* [16] and in *Principles of Neurocomputing for Science and Engineering* [17]. General searches on battery management systems were also carried out on the World Wide Web.

The papers cited in this report referenced other papers also reviewed in this report. This closing of the loop of references was used as an indicator that most applicable resources have been found in the course of this project.

3 RESULTS

This section of the report examines neural networks and fuzzy logic in battery management systems, but does not explain the independent concepts of each. For further explanation, readers are referred to discussions in the appendices on battery management systems (Appendix A), neural networks (Appendix B), fuzzy logic (Appendix C) and neuro-fuzzy systems (Appendix D).

The papers presented in this report show the advantages of using neural networks and fuzzy logic to model a system whose inherent mathematical model is difficult to extract. Previous attempts to find the mapping between the input variables and the output variables consisted of either correlation studies or least squares solutions to these models [9]. Unfortunately, the least squares solution, which is the ideal mapping for the problem, is not as effective in this case because the least squares solution can be implemented only at the end of a battery cycle when all the data has been gathered.

Hence one can only use solutions that are approximations of the ideal least squares mapping. The neural networks component of the proposed systems approximates the least squares solution to the model by using a stochastic gradient schema. Such approximations to the least squares solution have been well studied in the area of equalizer research [18, 19, and 20].

The BMS studied are presented in three groups based upon the method used to estimate the State-of-Charge (SOC)/State-of-Health (SOH) in the BMS. Section 3.1 deals with BMS that used only neural networks to measure the SOC/SOH. Section 3.2 deals with BMS that used fuzzy logic, possibly in conjunction with some other techniques, to measure the SOC/SOH. Section 3.3 deals with BMS that used neuro-fuzzy systems to measure the SOC/SOH.

3.1 Battery management using neural networks

Approximately half of the battery management systems studied relied solely on an artificial neural network to estimate the SOC/SOH of the battery. Solutions that combined other computational intelligence techniques were placed in the category of neuro-fuzzy systems. The following are summaries of the research groups that have used neural networks for modeling the battery.

3.1.1 Grewal et al. [21] implemented a three layer neural network with 7 nodes, trained as a function of the battery voltage and the load current. The input and output layers of this neural network used linear functions while the hidden layer used a sigmoid activation function. The network was trained using backpropogation on Li ion batteries. Fairly consistent results were obtained in which the discharge patterns were found to have continuous smooth characteristics.

3.1.2 Cai et al. [22] looked at the importance of selecting input variables for the neural network in estimating SOC. In particular, they summarized their findings for correlational analysis for selecting the input variables. They looked at using functions of the discharging current, discharging time and terminal voltage as inputs to the neural network. While these input variables themselves should allow us to converge to the right answer, using functions of the variables improves the rate of convergence and the accuracy of the convergence. Their final neural network gives values with absolute errors that are not more than 5% within 10 minutes of training. Cai et al [23] also looked at comparing the accuracy of a neural network with a conventional battery management system using Peukert's equations. They found that the performance of the neural network based estimator was better than all three versions of the Peukert's equation based estimator, having a smaller mean squared error and a smaller maximum error.

3.1.3 O'Gormon et al. [24] conducted preliminary studies on using neural networks to simulate battery behavior. They chose to implement a connectionist normalized linear spline (CNLS) network with a radial basis function set and a feedforward backpropogation algorithm. As seen in Figure 2, the predicted values match up closely with the actual values, for the different loads that the system was simulated under. While the team did not give estimates of the errors seen, they concluded that in their assessment the simulations closely matched with the results seen in the laboratory. Inaccuracies were found to be greater at points of rapid change, such as at the knee voltage when the battery has almost discharged.

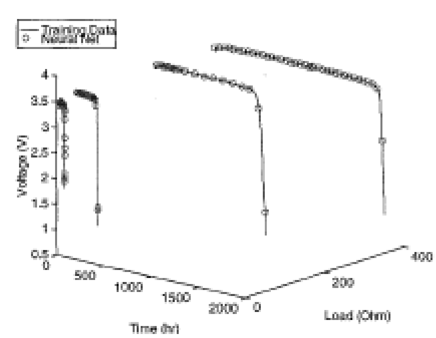

Figure 2: Simulations of different loads on a nonrecurrent CNLS [24]

3.1.4 Chan et al. [25] implemented a three layer neural network with backpropogation, linear activation functions at the input and output layers and a sigmoid activation function in the hidden layer. Their research was centered on the use of the lead acid battery in electrical vehicles. Based upon the discharge characteristics seen, they found their accuracy to be >99.5%.

3.1.5 Gerard et al. [9], at Laboratoires d'Electronique Phillips S.A.S., implemented two neural networks in a master slave relation to study rechargeable batteries in portable electronic equipment. They obtained a prediction accuracy of 3% (18 minutes). By using a third adaptive neural network, they further reduced the average error to 10 minutes. Gerard et al also studied the effect of the input variables and their non linear function mapping to the SOC [26]. They were one of the few groups to look at using the length of the last resting time as an input variable. By using a third online adaptive loop, they decreased the error, because this loop was able to mitigate the effects of aging on the prediction accuracy.

3.1.6 Yamazaki et al. [7] used neural networks with four inputs factors: terminal voltage, charge/discharge current, battery impedance and battery and air temperature. They used a sigmoid activation function for the neurons to normalize the distribution. The neural network had 50 hidden nodes and was trained using backpropogation. A mean error of 1.6% was obtained.

3.1.7 Urbina et al. [11] at Sandia National Laboratories modeled a photovoltaic (V) source and the connected battery using a Karhunen-Loeve framework. A Multivariate Polynomial Spline (neural) network, a generalization of the CNLS, was used to estimate the capacity of the battery studied and to estimate the SOH of the battery. The simulations of the battery damage caused in a deficit charge environment, such as PV, showed that the system was reliable for 1 year.

3.1.8 Peng et al. [27] implemented a three layer feedforward neural network for studying batteries in electric vehicles, with a modified Particle Swarm Optimization (PSO) algorithm used to train the neural network. The neural network was tested under different drive profiles in hybrid electric vehicles and the SOC was estimated within a range comparable to that of conventional models. The PSO algorithm was determined to be more capable of fine tuning than the backpropogation based algorithms. The model did not take into account the aging effect and did not look into SOH measurements.

3.1.9 Summary of Neural Network based BMS

Of the neural networks based BMS studied, results of different research groups were comparable. Most of the research groups focused on using a Multi Level Perceptron with backpropagation, utilizing the terminal voltage and charge/discharge current amongst other input variables. The work of Cai et al [22, 23] demonstrates the importance of choosing the right functions of these variables for the neural network. Two groups successfully implemented connectionist normalized linear spline neural networks, making it another candidate algorithm for a battery management system.

3.2 Battery management using fuzzy logic

Fuzzy controllers are generally not adequate to satisfactorily determine the SOC and SOH of a battery. In my research I found only one research group able to demonstrate a fuzzy solution that could determine the SOC and SOH of a battery.

Salkind et al. [28] used fuzzy logic to analyze data obtained by impedance spectroscopy and coulomb counting techniques. Data on primary lithium/sulfur dioxide cells and nickel/metal hydride cells were reinterpreted using this system. Previous authors had analysed electro-chemical impedance spectroscopy data by using a least squares fit to the data to extract the equivalent circuit parameters. The research of Salkind et al developed fuzzy models for this task, using both Mamdani and first-order Sugano models. A maximum absolute error of 5% was reported. While Salkind was able to achieve a good accuracy from this implementation, they concluded in their paper that the performance of the system would be improved by using a neural network to train the fuzzy logic.

3.3 Battery management using neuro-fuzzy systems

Most of the older papers on adaptive models for battery management designed systems with just one of these two modeling paradigms. The research undertaken in the last few years, however, clearly shows a trend towards using a combination of these fields in battery modeling. This transition towards using neuro-fuzzy logic is due to the advantages of using neuro-fuzzy systems to offset the limitations of either technique [29].

3.3.1 Goser et al. [30] derived a neuro-fuzzy schema in which a Kohonen Self Organizing Map (SOM) is used to train the data in a fuzzy system. The SOM, as the name implies, is a blind neural network that does not use a training signal. Instead a SOM looks at incoming information and seeks to organize itself. By using a SOM to feed a fuzzy system, the system is made both relative and adaptive. The architecture of the system implemented by Goser is shown in Figure 3. The fuzzification (also written as fuzzifikation) is split into two layers of inputs, leading to the rule base and then subsequently to defuzzification. This seven layer network is then trained in part by using neural network algorithms.

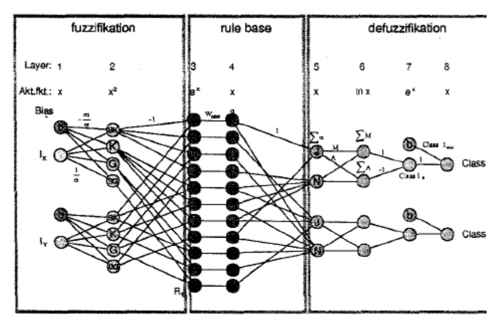

Figure 3: Architecture of an integrated neuro-fuzzy system [30]

3.3.2 Buchmann et al. [31] at Cadex Electronics implemented a neuro-fuzzy based battery management system that can track the battery SOH in three minutes. The neural network was trained on fuzzified data, and the outputs then defuzzified. The exact algorithm was not described in the paper.

3.3.3 Ullah et al. [32] at National Semiconductor Corporation implemented a neuro-fuzzy system to control the charging of a battery. This algorithm, called NeuFuz, monitors the battery to determine the charge current for the battery. The algorithm was tested in a nickel cadmium battery and found to be capable of charging a battery within 20 to 30 min as compared to 1 to 1.5 hours with a conventional charger. The algorithm was also shown to be extensible to other types of batteries.

3.3.4 Summary of Neuro-fuzzy system based BMS

Goser et al. used a neural network to feed the data into fuzzy systems that formed the BMS [30]. Goser found these systems were able to self organize the information allowing the BMS to be designed independent of the type of battery used. This is a benefit that was not reported by other groups, since it allows for the same system to be used with different kinds of batteries.

It was expected that the performance of BMS with neuro-fuzzy systems would be superior to those with neural networks only. However, the performance of the different implementations could not be compared since they did not report quantitative estimates of their accuracy and hence the research was inconclusive.

The research on neuro-fuzzy systems is also not comprehensive. Two out of the three papers cited implemented proprietary algorithms that were not described in the paper. This lack of knowledge of past implementations makes future research on neuro-fuzzy systems more difficult.

4. Conclusions

Battery management has come a long way from the time of constant current chargers that did not attempt to monitor the battery to modern neural networks based models. In the cited research, all researchers found better results in using neural networks and fuzzy logic in their BMS. The systems described also performed better at accounting for the aging effect and adapting to the battery being monitored.

Although the battery management systems studied showed improved performance, no field studies were conducted that would indicate the robustness of the developed algorithms. Robustness to noise is an important prerequisite for any candidate battery management system because batteries are usually subject to environmental influences that show up as noise. The range of error reported, between 0.1% and 10%, cannot be placed in context without comparative studies that take environmental noise into account.

No clear metric exists for reporting the accuracy of the algorithms in measuring either the SOC or the SOH. The range of the error reported may indicate the different metrics used in the measurement of the error more than in the differences between the algorithms themselves. Without such a metric, a thorough comparison of the different systems can not be undertaken. Hence there is an urgent need for a clear specification that would describe a common semantic framework for the field.

While the algorithms used by the groups implementing the neural networks based solutions were easily compared, two of the three research groups building neuro fuzzy implementations for their BMS used proprietary algorithms that were not described in the papers. This made it difficult to compare the neuro-fuzzy implementations. Further, except for the work of Goser et al., the absence of documentation on the algorithms used is expected to make further research more difficult.

Further research also depends on recognizing the interdisciplinary nature of the field. Experts in neural networks tended to publish in the IEEE journals, while experts in the field of battery management published in the *Journal of Power Sources*. This study found that papers in the IEEE journals did not cite the relevant papers in the *Journal of Power Sources*, and vice versa. As a result, few papers compared their results to those obtained by other researchers, and the results and conclusions were focused solely on their particular algorithm, without a discussion of more general insights obtained through their research.

None of these shortcomings, however, should distract our attention from the promise held out by neural networks and fuzzy logic for modeling of battery management systems. Increased efficiency in battery modeling is essential to power management strategies and is expected to be a dominant factor in the design of portable electronics. Of all current research in this field, neural networks and fuzzy logic are in the best position to provide such an increase in efficiency.

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GLOSSARY

Adaptive refers to the property of adapting to changing (battery) conditions.

Capacity is the time integral of the current delivered to a load before the terminal voltage drops below the specified End of Discharge (EOD) voltage.

Correlation is the degree of association between two or more quantities.

Correlation coefficient is a quantity which gives the quality of a least squares fitting to the original data.

Distributed refers to the local nature of the management system, where each component of the management system is located close to the battery itself.

Embedded here refers to the software and hardware that is designed expressly for battery management and located (physically) with the hardware.

Fuzzy Logic is a field that is best characterized by the theory of "fuzzy" sets. A normal set is linked to the "common sense" or intuitive feel for a set as being a grouping where an element is either in the grouping or is out of the grouping. In contrast, a fuzzy set has elements, which are allowed to be partially in the set and partially out. As a consequence, fuzzy logic is better able to capture systems where there are "relative" factors that have changing levels of importance.

Least squares is a mathematical model for fitting the best curve to a given data set to minimize the sum of the squares of the offsets (or residuals) to those points from the curve.

Maximum Error is a measure of accuracy for an estimation of a system. The maximum error is the maximum of the absolute difference between the predicted and the actual values.

Mean Squared Error (MSE) is a measure of accuracy for an estimation of a system. The MSE is the average of the difference between the predicted and actual values squared.

Neural networks are systems that respond adaptively to changing environments. These systems can also have elements that retain the "memory" of past values that were sent in (inputs) or given out (outputs).

Relative refers to a property of being used in a fuzzy logic controller (being within the fuzzy set) for certain conditions. The degree in the fuzzy set (membership function) is considered the "relative ness" of the given factor.

State of Charge (SOC) is the ratio of the remaining capacity to the initial (rated) capacity of the battery.

State of Health (SOH) is the condition of the battery and is defined as the remaining lifetime of the battery and the initial (rated) lifetime of the battery.

Terminal Voltage is the voltage across the terminals of the battery when an infinite load is present across the battery.

Definitions of mathematical terms – correlation, correlation coefficient and least squares, were taken from http://mathworld.wolfram.com.

APPENDICES

Appendix A: Battery Management

Battery management system (BMS) refers to software and hardware designed to maximize each discharge cycle of the battery while maximizing the lifetime of the battery [1]. In particular, there are two important variables that I refer to in the report – State of Charge (SOC) and State of Health (SOH). The first, SOC refers to the amount of charge present in a battery at a given point in time. Hence it represents in a given battery in a charge or discharge cycle. The second, SOH represents the performance of the battery compared to its past and expected future.

Neither SOC nor SOH are directly measurable and need to be inferred from other measurements. To assess the SOC and the SOH of a battery, there are four classes of methods used. The first class of methods involves making appraisals of the battery components, such as measuring the specific gravity of the electrolyte. A second class of methods involves making physical measurements, which are then compared to an observed relationship between the measured value and either the SOC or the SOH. A third class of methods involves using the Peukert's equation for battery capacity, or a derivative of this equation, which relates the capacity of the battery to the current and the temperature. The fourth class of methods uses a measurement of the charge being transferred across the battery to infer SOC and SOH and control the charging and discharging of the battery [32].

The first class of methods is the least sophisticated and is seldom used in a high performance situation. The second class of methods uses parameters of the battery that can be measured directly, such as the terminal voltage and the internal impedance of the battery. The measurements of the terminal voltage, the voltage present when the battery is in open circuit, form a stochastic process, which must be averaged and then correlated with the measurements of a representative sample. The results of these correlations allow us to deduce the capacity of the battery and hence assign a value to either the SOC or the SOH of the battery. The correlation coefficient is then used in further predictions for the battery.

The third class of methods employs the Peukert's Equation for battery capacity as presented below (in its simpler form):

$$\text{Capacity} = \text{Coeff} \times I^{\exp} \qquad (1)$$

where I = current (A)
Capacity = battery capacity (Ah)
Coeff = constant coefficient, empirically derived,
exp = constant exponent, empirically derived.

For simplicity, the version of Peukert's equation shown does not account for the temperature of the battery, usually a feature of the more complex models used in the industry.

As seen in Equation 1, certain terms of the equation are derived empirically from the data measured in the laboratory. Without loss of generality, this process can be equated to the correlation of the two factors, current and battery capacity. The complete equation, with the constants measured by testing batteries in laboratories, is used to model the battery and measurements of the current are fed into the equation to get the remaining battery capacity [7].

The fourth class of methods, counting the amount of charge that enters and exits the battery, has two shortfalls. First, this method implies perfect conversion of charge and energy efficiency since the amount of charge entering has to equal the amount of charge leaving. The chemical changes in the battery don't always satisfy this criterion since the process of charging the battery also leads to a certain degree of chemical degradation. Second, the process is dependent on the accuracy of the current integration.

These difficulties with modeling batteries stem from the battery being non linear and time variant. Time variant, as opposed to time invariant refers to the fact that the battery is affected by its history and depends upon the charge cycles before the present cycle. Conventionally, control logic has been developed for linear time invariant (LTI) systems. To model the battery, the control logic then seeks to parameterize the battery and reduce both the non-linearity and the time variance. That is by looking at a small interval, the control logic makes an approximation of the battery being LTI. As seen in Figure 4, the parameters of any battery are weak indicators of the state of the battery. The history and state of charge of the battery are important to place this information in context and these are the pieces of information that make it possible for the rest of the system to model the battery as being LTI. Furthermore, a small error made in measuring either the SOC or the SOH also affects the measurement of other variables, thereby significantly affecting the accuracy of the entire model [9].

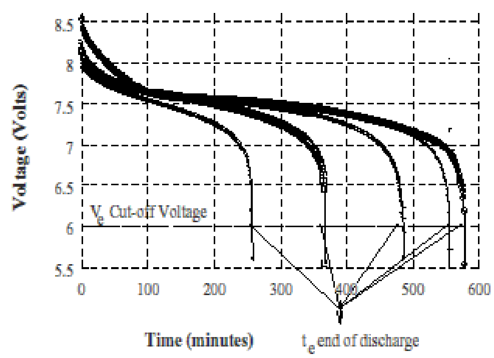

Figure 4: Relationship between the terminal voltage and the SOC (or end of discharge) [9].

Appendix B: Neural Networks

Neural networks are mathematical models that are also concerned with processing information. They involve a different approach to information processing than "programmed computing" by involving "a learning process" that "adaptively responds to inputs according to a training rule". The neural network stores the "knowledge that has been learnt in the synaptic weights of the neurons" [26].

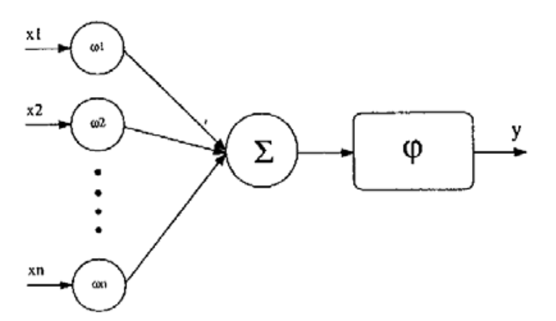

Figure 5: Model of a simple perceptron [7].

A simple perceptron is a basic neural network (Figure 5). The inputs {X1, X2 … Xn} are the pieces of information (input vector, {X}) entering the neural network from the environment. For instance, the input vector could represent a stationary random process which is a particular example of a time indexed vector of random variables. Hence, Xn would represent the variable at time n, and Xn-1 would represent this variable at time n-1. X1 thus refers to the random variable at time X1. These inputs to the simple perceptron are weighted (by the weight vector, {W} = {W1… Wn}) and then summed (represented by the circle with the ∑ symbol). This weighted sum of the input vector is passed to φ, the "activation function" of the neural network. The simplest activation function is the hard limited binary function. This function has an output of one when the sum of the weighted inputs exceeds the activation function threshold and an output of zero otherwise. The most commonly used activation function is the sigmoid function, which is used to normalize for the summing.

Continuing the example of the input vector, {X} being a stationary random process, the expected values for the system are based upon the weight vector {W}. In the simplest version of the process of training the Perceptron, {W} is updated by using the difference between the output and the expected output (the error). This difference between the expected output (the training signal) and the output is used to update the weight vector and hence converge (over a number of terms) to a form that reduces the error.

Multi Level Perceptron (MLP) is a neural network that is an extension of the simple Perceptron. MLP have more than one layer of neurons. The first layer is known as the input layer, and the last layer is known as the output layer. The layers in the middle of the neural network are known as the hidden layers. For example, Figure 6 shows a neural network (also known as an artificial neural network, or ANN) used to model battery management. This example, from a paper on modeling Ni-MH batteries, uses a MLP with back-propagation (BP). BP is a commonly used mechanism for training a MLP. Like the case of the simple Perceptron, the error between the output and the expected output can be used to train the network. With backpropagation, as the name implies, the error function is propagated backwards through the network. Hence, the error (difference between expected output and current output) is used to train the output layer. A modified version of this error is then used to train the layer of neurons just above the output layer. This process is repeated until we reach the input layer which is trained by the layer directly underneath it. Hence, in Figure 6, if we trace the flow of information we see that the measured current, i(k+1) is sent into the battery and into the ANN model. The predicted output of the voltage, v'(k+1) is then compared to the actual output v(k+1). This result of the neural network is used to train the output layer of the MLP. The error function is then propagated through the hidden layer and the input layer, thus training the entire network.

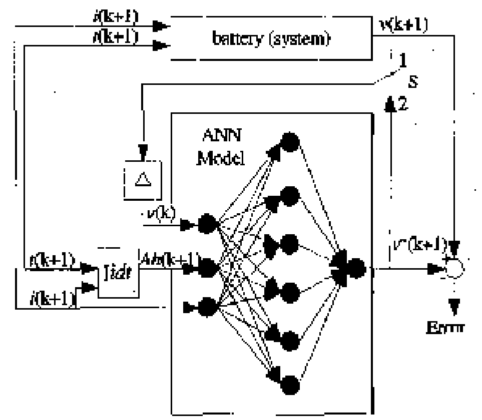

Figure 6: Schema for estimating SOC and SOH by using a neural network [22].

Appendix C: Fuzzy Logic

Fuzzy logic is a way of representing information that mimics human reasoning about information. The theory of fuzzy logic is based upon fuzzy sets and is designed to model systems where there are relative factors that have changing levels of importance. In fuzzy logic, unlike standard Boolean logic, all variables need not subscribe to the on-off model where each variable is either a 0 or a 1. This fact follows from the theory of fuzzy sets, and it would be helpful to briefly discuss fuzzy sets.

A normal set is linked to an understanding of the set as a group of elements. As an example let us take three "things": apples, spinach and tomatoes, and two "categories": fruits and vegetables. In everyday parlance, the apples are fruits and spinach is a vegetable. Similarly, in conventional set theory, the apple could be either assigned to the set of fruits and the spinach to the set of vegetables.

This is a represented by using the membership function, M, where if an element of the set has a membership function of 1, denoted by M (element; set) = 1. Conversely, for elements not in the set, the membership function is given the value of zero. In our example,

M(apple; fruit) =1 ; M(apple; vegetable) = 0

M(spinach; fruit) = 0; M(spinach, vegetable) = 1

The difficulty with this approach is borne out by the case of the tomato, which is technically a fruit of the vine plant, but is commonly considered a vegetable. Using conventional sets, one could call it a member of either of the sets or possibly of both the sets. However, this loses that essential information that the tomato is partly a fruit and partly a vegetable.

To keep this information we turn to fuzzy sets. A fuzzy set has elements that can be partially in the set and partially out and the membership function of a fuzzy set, unlike the normal set, can be fractional. Hence, in this example, the tomato can be partly in the fuzzy set of fruits and partly in the set of vegetables.

Extending the vernacular for the control system we want to use fuzzy logic with, we can then define inputs as being crisp. The crisp inputs are mapped through various membership functions to fuzzy inputs, a process known as fuzzification. The fuzzy inputs are then acted on by the inference rules, a set of rules which operate on the input variables and determine the fuzzy outputs of the system. In the final step, the fuzzy outputs are converted into crisp outputs, a step called defuzzification.

The fuzzy controller hence has two separate entities that can be changed to tune the controller – the membership functions and the set of inference rules. Neural networks and other computational intelligence techniques are used to train these entities, forming neuro-fuzzy networks [33].

It is important to note that there are two types of fuzzy controllers mentioned in the report, the constructive (Mamdani –type) and the destructive type. The details of these controllers are beyond the scope of this report and the reader is directed to [16], where each of these controllers is discussed in greater detail.

Appendix D: Neuro-fuzzy systems

There are many forms of neuro-fuzzy logic, formed by combining different types of neural networks and fuzzy logic systems. This convergence of the two fields is a natural result of their genesis. Neural networks were derived from neuroscience and in particular from neurons, the fundamental units of our brain. In this respect, neural networks can be considered as being based on the actual means of processing information. Fuzzy logic on the other hand was based upon the way we represent information and is meant to represent human reasoning about information. It is this difference in their primary form that makes the combination of neural networks and fuzzy logic systems, neuro-fuzzy systems, better at representing complex systems [33].

Nauck et al [29] studied the effect of using neural networks on fuzzy sets. He used a Multi Layer Perceptron to train the membership function of a fuzzy logic system. Both Mamdani and Sugeno type fuzzy controllers were trained using neural networks. In another form of the studied neuro-fuzzy systems, Nauck used input-output pairs from the fuzzy system as inputs to a Kohonen SOM.

The convergence of neural networks and fuzzy logic poses substantial difficulties. First, the diverse mathematical foundations of neural networks and fuzzy theory are less well defined in their overlapping aspects than when studying each separately. Second, neural networks need to be fine-tuned for the given application since the complexity of the underlying theory frequently makes the computation of the step-sizes (constants used in the algorithm to update the neural network) intractable. Third, both fuzzy logic and neural networks present cases in which noise makes the system diverge and lose track of the variables presented. Robustness to noise is thus an important area of research in this field [33].