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Design and Development of a Fuzzy Based IVT Sensor for Battery Management System to Monitor SOC in Power Conversion Applications

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Abstract:
The battery management system (BMS) of a hybrid-electric-vehicle (HEV) battery pack comprises of hardware and software to monitor pack status and optimize performance. One of its important functions is to execute algorithms that continuously estimate battery state-of-charge (SOC) and available power. The accuracy of these algorithms is critical for the proper sizing of the battery pack .If accurate algorithms are not available, the pack—already among the costliest and heaviest components of the propulsion system—must be over-designed to compensate. This project presents a very accurately estimate the desired quantities through Fuzzy logic. While the algorithms are mathematically advanced, they can be implemented on simple and inexpensive micro-controllers. The result is an important element of an economical, robust, and reliable HEV energy storage system

Keywords: *State of charge, fuzzy logic, microcontroller, battery management system*

1. Introduction

Most battery management systems require calculation of battery state of charge (SOC) and may also require battery state of health (SOH). When the IVT sensor is integrated into a vehicle along with active battery management, the system can deliver improved fuel economy, increased battery life, and increased energy system availability. Battery management reduces fuel consumption when the IVT/Battery management system is equipped with alternator voltage output control as part of the system. Many battery powered applications required knowledge of the State of Charge (SOC) of the battery or of the individual cells in the battery chain. This may simply be for providing the user with an indication of the capacity left in the battery, or it could be needed in a control circuit to ensure optimum control of the charging process. Knowing the amount of energy left in the battery is compared with the amount of energy present when the battery is full gives the information regarding the battery life that is how long it can be alive before it has to recharge.

2. SOC Determination

Knowing the amount of energy left in a battery compared with the energy it had when it was full gives the user an indication of how much longer a battery will continue to perform before it needs recharging. Using the analogy of a fuel tank in a car, State of Charge (SOC) estimation is often called the "Gas Gauge" or "Fuel Gauge" function.

The SOC is defined as the available capacity expressed as a percentage of some reference, sometimes its rated capacity but more likely its current (i.e. at the latest charge-discharge cycle) capacity but this ambiguity can lead to confusion and errors. It is not usually an absolute measure in Coulombs, kWh or Ah of the energy left in the battery which would be less confusing. The preferred SOC reference should be the rated capacity of a new cell rather than the current capacity of the cell. This is because the cell capacity gradually reduces as the cell ages. For example, towards the end of the cell's life its actual capacity will be approaching only 80% of its rated capacity and in this case, even if the cell were fully charged, its SOC would only be 80% of its rated capacity. Temperature and discharge rate effects reduce the effective capacity even further. This difference in reference points is important if the user is depending on the SOC estimation as he would in a real gas gauge application in a car

In EV applications the SOC is used to determine range. It should be an absolute value based on capacity of the battery when new, not a percentage of current capacity which could result in an error of 20% or more due to battery ageing. Automotive fuel guages are notoriously imprecise so an SOC accuracy of 5%, if it could be achieved, would probably be satisfactory for such applications.

In HEV applications the SOC determines when the engine is switched on and off. SOC errors over 5% could seriously affect the system fuel efficiency. An accuracy significantly better than 5% is therefore desirable.

The following are several kinds of common state of charge estimation: (a) Open Circuit Voltage SOC (b) Load Voltage SOC (c) Coulomb SOC (d) Internal Resistance SOC (e) Specific Gravity SOC

2.1. Open Circuit Voltage SOC

The so-called open circuit voltage measures voltages of two poles of a battery which do not load to estimate its state of charge. As in Fig 1, the open circuit voltage of a Lead-Acid battery and charge storing inside the battery are close to linear proportion. The higher the open circuit voltage, the more charge of the battery is. When the user measures open circuit voltage of the battery, then have to open load, and put the battery for a while so that the thickness of electrolyte distributes well-mixed. Then the user will get correct voltage data. But for the battery in using, the user can not open load, let along putting the battery for a while. Thus, although the user can get high accuracy of stage of charge with open circuit voltage, it's limited in truly applying, so the user has to combine other methods to strength the method.[1]

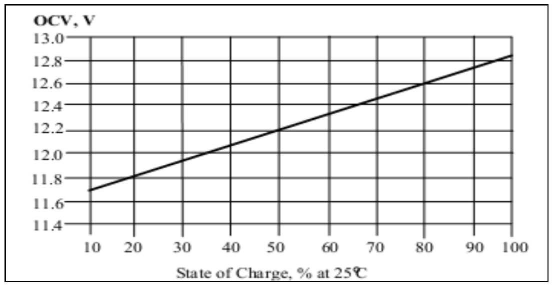


Figure 1: Relationship between open circuit voltage and SOC

2.2. Load Voltage SOC

The user can get quite high accuracy by using open circuit voltage to measure state of charge, but a battery in using can not be opened load and put for a while, so the user can use load voltage to measure state of charge to solve the problem. The Fig.2, is a figure of relationship between load voltage and state of charge when a Lead-Acid battery discharges with constant current. We can learn from the figure the voltage of the battery will decrease with the increasing of discharging time, and the curve changes in linear. The voltage will decrease fast and suddenly when it is lower than knee voltage, and this means the charge of the battery will exhaust. In using, the user can neglect it because charge after knee voltage is fairly few and the change of voltage is too high, which can cause problems for the equipments. If the user uses knee voltage for discharge end voltage, and uses lineal curve before the discharge end voltage to predict state of charge, Load Voltage has the advantages of being simple and cheap; but to changing load of unfixed discharge current, it will cause quite large error value. So Load Voltage SOC is suited for cheap and low accurate using, and it is one of the more extensive methods.

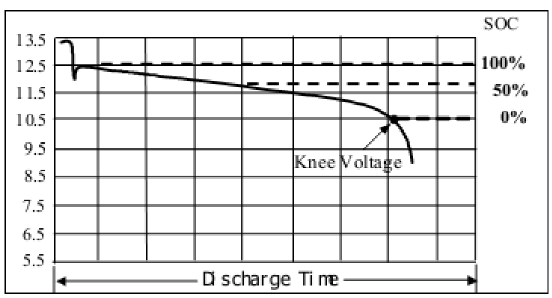


Figure 2: Relationship between load voltage and SOC

2.3. Coulomb SOC

Coulomb SOC is using ampere-hour for total charge of discharge and charge to calculate. It bases on and uses in charging to subtract in discharging, and then the user can get the charge left in the battery, so it's also called.

The calculation method is as the following:

NEW SOC (Ah) = OLD SOC (Ah) ± Charge of Discharge or Charge (Ah)

But the internal resistance of the battery will affect the battery when it discharges, causing charge of discharge and discharge current to have a relationship of inverse proportion, which means the higher the discharge current, the less charge of discharge will have. Besides, Coulomb SOC calculates by adding up, which is easy to accumulate error value, so both the above factors will cause Coulomb SOC to have high error value. So Coulomb SOC has to combine other methods such as Load Voltage SOC or Open Circuit Voltage SOC to improve accuracy of prediction

2.4. Internal Resistance SOC

An internal resistance of a battery has two meanings. One is an ohm resistance, and the other is produced with polarizing in an electric chemical reaction. In the latter, its resistant value will change with the thickness of electrolyte which is decided by the charge inside the battery, so the internal resistance will decrease with the increasing of the charge when the battery charges. The internal resistance will increase when discharging because the thickness of electrolyte of the battery decreases, and produced by the chemical reaction is a non-conductor that causes resistance between the electrolyte and the plate. Therefore, Internal Resistance estimates the state of charge of a battery by measuring the changing of its internal resistance in charging and discharging, which is as illustrated in Fig. 3. But because the changing of the internal resistance inside the battery is very little, the equipment measuring the internal resistance needs high accuracy and precision. Besides, the internal resistance of the battery will have non-linear changing because the aging of a battery, which not only affects the accuracy of the detecting but also makes it hard for the user to correct and adjust. So it's very tough to get accurate state of charge by using the internal resistance. [1]

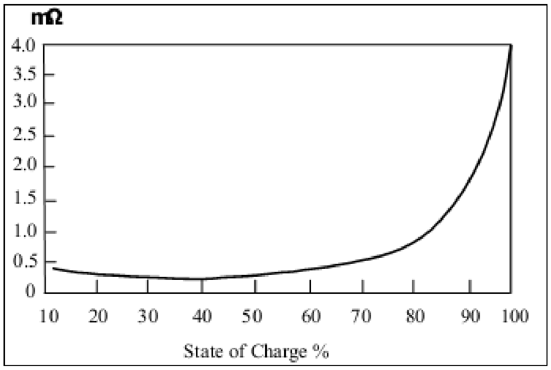


Figure 3: Relationship between internal resistance and SOC

2.5. Specific Gravity SOC

Because discharging and charging is caused by electric chemical reaction, we can learn from that sulfuric acid in the electrolyte will decrease gradually after the reaction and water will come out, which decreases the thickness of sulfuric acid. But it is on the contrary in charging because the thickness of sulfuric acid in the electrolyte will increase gradually with charging time, causing increasing of the thickness of sulfuric acid. We can learn from the above changing that the thickness of sulfuric acid in the battery relates the amount of charge. Therefore, the user can judge state of charge by measuring specific gravity of electrolyte, and the curve of the relationship of thickness of electrolyte and state of charge is illustrate as Fig.4.We can see linear relationship between electrolyte and state of charge from the curve of the figure. But in discharging and charging, electrolyte with high specific gravity will sink, and above part of the electrolyte has lower specific gravity than below part of it. So the user has to put the electrolyte for a while waiting for it to spread and mix well and then can get correct specific gravity value. Besides, the user has to open the shell of the battery when installing because it relates user's safety and convenience when using a battery.[1]

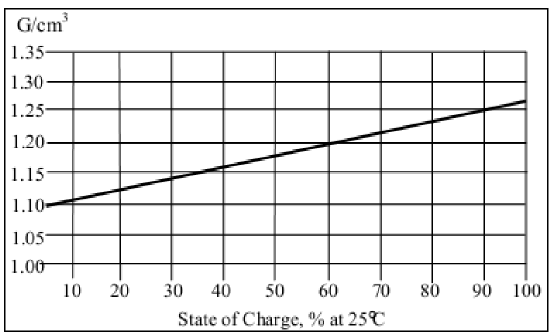


Figure 4: Relationship between specific gravity and SOC

3. Design Implementation

3.1. Hardware Implementation

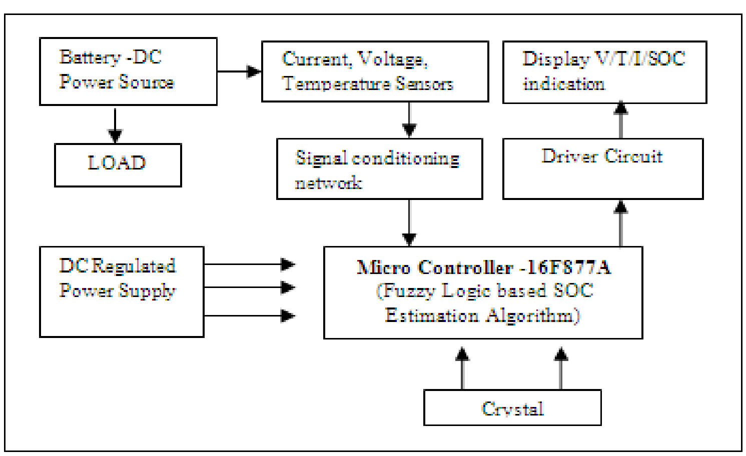


Figure 5: Functional block diagram

Most battery management systems require calculation of battery state of charge (SOC) and may also require battery state of health (SOH). When the IVT sensor is integrated into a vehicle along with active battery management, the system can deliver improved fuel economy, increased battery life, and increased energy system availability. Battery management reduces fuel consumption when the IVT/Battery management system is equipped with alternator voltage output control as part of the system. The realization of Fuzzy based IVT sensor for battery management system to monitor SOC is realized using a microcontroller 16F877A based system which monitors the I/V/T of a lead acid battery, estimates SOC of the battery and displays on a LCD display panel.

3.2. Introduction to Fuzzy Logic

Data may be characterized in two ways: crisp or fuzzy. Crisp data describes data that is certainly indicated, e.g., a temperature of 50 °C. On the other hand fuzzy data is indicated in an uncertain way, *e.g.*, the temperature is "warm". The linguistic descriptor can cover a range of temperatures and the degree to which a crisp data point falls into the fuzzy set of "warm" is indicated by a quantity referred to as its "degree of membership" to the set "warm". Consider the range of possible temperature values as a set of all temperature. A subset of temperatures can be defined as the set of all temperatures between 20°C and 30°C. Let this subset be referred to as the set of HOT temperatures. Obviously, a measured temperature value of 25°C can be categorized as a HOT temperature. [11]

Not so obvious is a measured temperature value of 22.5°C. Is this still a HOT temperature? If so, does it belong to the set of HOT temperatures as much as 25°C? Bivalent set or crisp set theory says yes. Not only is 22.5°C a HOT temperature, but the degree to which it belongs to the set of HOT temperatures, or its membership value or bit value (binary unit), is identical to that of 25°C, both a value of one. It would have to be in accordance with the '1-0' theory, *i.e.*, either a one or a zero. In contrast, a fuzzy set of HOT temperatures can be defined. This fuzzy subset can cover a range of temperatures as did the bivalent set, but now the degree to which a measured data point falls into the fuzzy set of HOT is indicated by a fit value (fuzzy unit) between zero and one.

The fit value is sometimes called the degree of membership. Fig.6 shows examples of various fuzzy subsets or membership functions of the temperature. Depicted is the degree of membership of various temperatures to the fuzzy subsets COLD, WARM and HOT. The process of assigning membership functions to sets of data is referred to as fuzzification of the data.

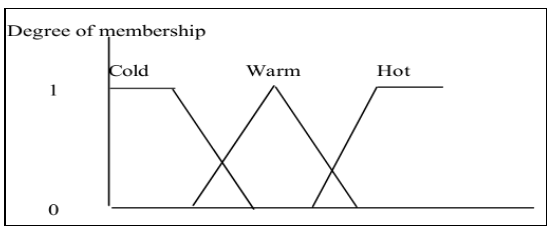


Figure 6: Membership function for temperature

Fuzzy set theory provides a method to categorize measured data using linguistic variables such as cold, warm and hot. It accounts for the uncertainty inherent in such a linguistic description by using multi valued sets Fuzzy systems map measured inputs to desired outputs. They estimate functions by translating the behavior of the system into fuzzy sets and by using rules based on a linguistic representation of export knowledge to process the fuzzy data. This offers a qualitative rather than a numerical description of a system. The linguistic representation presents an intuitive, natural description of a system allowing for relatively easy algorithm development compared to numerical systems. The ease of development of fuzzy logic systems should not undermine their powerful capabilities in solving complex control and modeling problems.

A typical fuzzy system has four conceptual components:

· A rule base describing the relationship between input and output variables;

· A data base that defines the membership functions for the input and in the case of Mamdani modeling output variables;

· A reasoning mechanism that performs the inference procedure;

· A de-fuzzification block that transforms the fuzzy output sets to a real valued output. The rules relating the input and output variables are written in an 'if… then' linguistic format, such as 'if temperature is hot and discharge rate is high then SOC is low'. The membership functions and rule set may be described by an expert or generated by the use of neural network algorithms. Unsupervised neural networks, such as the subtractive clustering algorithm, can find the initial rules and membership functions using numerical training data that describes the input/output relationship[11]

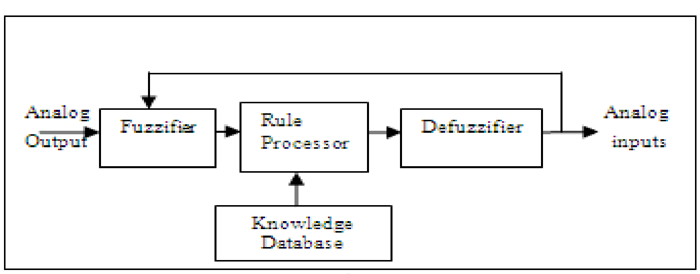


Figure7: Complete Fuzzy system

3.3. Software Implementation

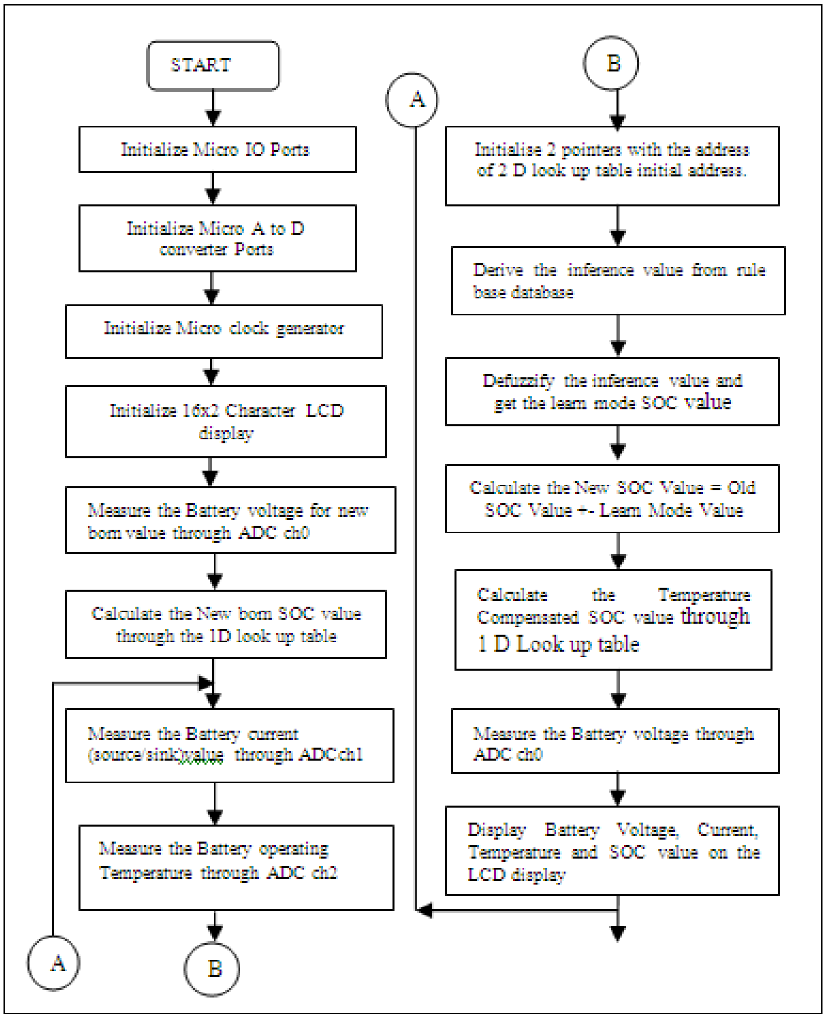


Figure 8: Flow chart

4. Testing and Result

Integrated Power supply circuit , battery and sensor circuit with the Microcontroller board When the set up is switched on LCD displays the Voltage ,Negative Current for charging and positive current for discharging ,Temperature and State of Charge in percentage of 12V 7.5 AH lead acid battery Discharging is observed with connecting 11W lamp load and charging by disconnecting the load . Found 12 volt at rectifier terminal for battery charging and 5 volt out put at the regulated power supply for the micro controller.

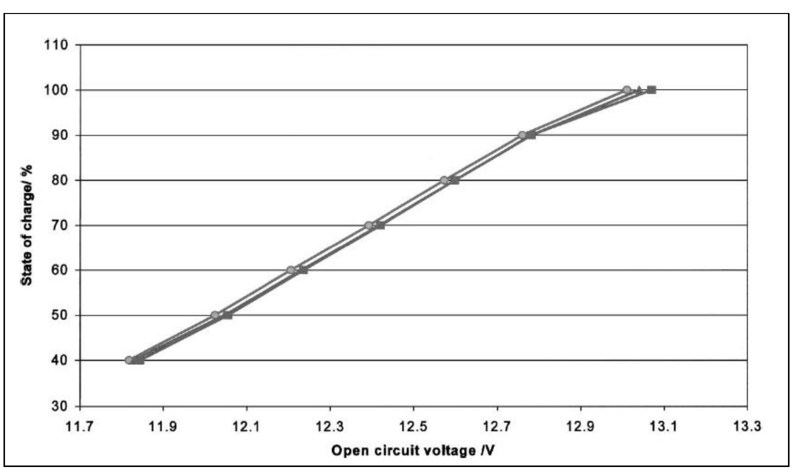
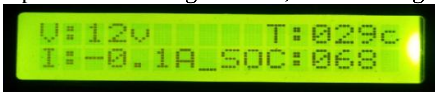


Figure 9: Open circuit voltage Vs SOC

4.1. Observation according to the graph

Open circuit voltage of 12V, self discharging at 0.1A and SOC 68% at 29ºC



On charging voltage reaches to 12V with 0.4A and SOC increases to 57% at 33ºC

On charging voltage reaches to 13V with 0.2A and SOC increases to 99% at 30ºC

On load of 11W bulb, voltage is 12V, discharging at 0.9A and SOC decreases to 39% at 28ºC

5. Conclusion

Presented Online SOC estimation, and monitoring of sealed lead–acid batteries during both discharge and charge periods. Available capacity of the battery is also estimated at the end of each charge and each discharge period.. This technique is successfully implemented, and tested. It is shown to be valid for various operating conditions in practice, including different charge –discharge rates and strategies, variable load conditions, different ambient temperatures, aged cells, different initial SOCs, and remaining capacities of sealed lead–acid batteries. Accuracy in SOC estimation better than 3% –4% has been obtained for all operating conditions. Discrepancies between monitored and theoretical SOCs are due to measurement/resolution errors and slight differences between manufacturer's characteristics. The proposed monitoring system has the advantage of easy implementation by software on a simple microcontroller, with minimum hardware requirement. It can be generalized to some other applications employing lead –acid batteries, such as uninterruptible power supply (UPS) systems, emergency power, solar-photovoltaic systems, submarine service, etc., with slight modifications in design due to possible changes in battery characteristics and manufacturers' data.

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