

# Evidence Theory Based Automotive Battery Health Monitoring

2010-01-0251

Published  
04/12/2010

Kwang-Keun Shin and Mutasim A. Salman  
General Motors R&D

Copyright © 2010 SAE International

## ABSTRACT

As the number of electrical devices in modern vehicles increases, the battery becomes more critical component for the operation of vehicles. To ensure the startability of the vehicle, battery conditions such as state of charge and state of health should be properly monitored and maintained. To reduce walk-home incidents due to no-start situation, appropriate warning should be issued to the driver to advise necessary actions such as replacing or re-charging the battery. For the last couple of years, General Motors has studied and developed several battery health monitoring methods based on different battery health signatures. Yet, it is found that relying on a single method may lead to false alarm or misdetection due to lack of information or uncertainty. This paper develops the algorithm for more robust and reliable battery health monitoring and prognosis, by applying Evidence Theory to fuse different battery health signatures. The algorithm is evaluated by using battery cranking data from the set of batteries collected from field. The test results show reliable and robust performance.

## INTRODUCTION

As the number of electrical devices in modern vehicles increases, the electrical power system becomes more critical for the operation of vehicles. The vehicle electrical power system is required to provide power not only to traditional needs such as starting, lighting, and ignition (SLI), but also to safety systems including electrical power steering, anti-lock braking, stability control, and airbag, as well as comfort and convenience systems such as air conditioning, seat heating, audio, video, and OnStar.

The electrical power is provided by either battery or generator. While engine is running, the power is mainly provided by generator, and battery is charged unless the

power demand exceeds the supply from the generator. When engine is not running, the battery is the only source of electrical power and the state of charge and the state of health of the battery directly affect the startability of vehicles. The no-start situation should be avoided by keeping the state of charge above certain level, and by warning the driver to replace the battery in advance if the battery is near the end of its life. Therefore, the battery health monitoring is an important part of the effort to improve vehicle quality and reliability, and to reduce warranty cost.

For the last couple of years, GM has studied and developed several battery health monitoring methods [1,2,3] based on different battery health signatures such as minimum voltage, average cranking power, battery resistance, cranking voltage characteristics, and parity residual. These signatures are somehow related but provide slightly different information about battery health. Relying on a single signature might lead to false alarm or mis-detection of battery state of health. To obtain a robust and reliable battery state, those pieces of information from different signatures need to be fused or combined. One methodology that makes this combination of information possible is so called Evidence Theory.

The Evidence theory, or Dempster-Shafer Theory in different name, has been used in many applications such as pattern recognition, sensor fusion, and design optimization [4,5,6,7,8], and is known to be very effective reducing the uncertainties of imprecise information gathered from different information sources. Each source of information provides a piece of information, called evidence, which supports certain hypothesis. But the information has some amount of uncertainty or error. However, by combining uncertain pieces of information from different sources together, the uncertainty can be reduced. The Evidence theory is a mathematical framework that enables fusion of uncertain information from different sources.

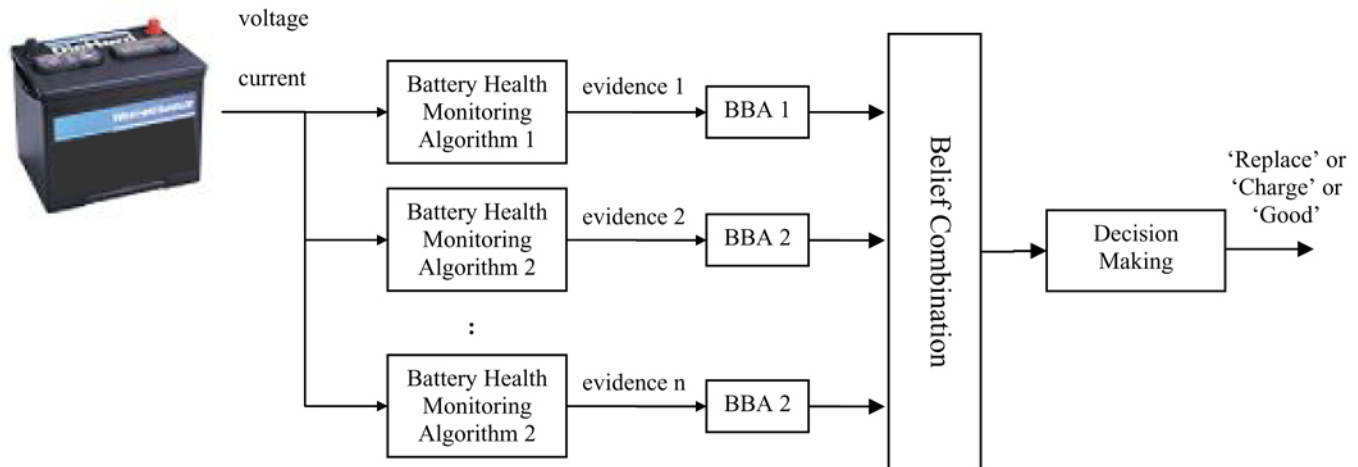


**Figure 1. Structure of Evidence Theory Based Battery Health Monitoring**

This paper adopts Evidence theory to enhance battery health monitoring algorithm for more robust and reliable results by reducing the uncertainties from individual battery health monitoring algorithm. The paper first formulates battery health monitoring problem in the framework of evidence theory. Then the paper discusses the process called basic belief assignment that converts information from each battery health signature into a mathematical object called belief vector. Finally, the paper demonstrates the effectiveness of the method by off-line evaluation, through the battery data collected from the field.

## EVIDENCE THEORY AND ALGORITHM

The purpose of the battery health monitoring is to determine battery condition, and to prevent no-start situation before it actually happens. The final outcome of battery health monitoring algorithm is then either 'Replace', 'Charge', or 'Good'. 'Replace' means the battery is near the end of its life and needs to be replaced. 'Charge' means the battery charge level is low and needs to be charged but there is no need to replace it. 'Good' means the battery is in good health and charge condition and no action is required.

To determine the battery condition, voltage, current and temperature of the battery during cranking are measured every cranking event. These raw signals are processed to extract battery health signatures such as state of charge (SOC), cranking resistance, average cranking power, minimum voltage, etc. These signatures are good indications of battery status. For example, cranking resistance higher than certain threshold is indication of bad health, and low cranking power is indication of either low SOC or bad health, etc. In evidence theory, these battery health signatures are translated into evidences that support certain hypothesis

about battery status. For the rest of the paper the term cranking signature means evidence.

<figure 1 here>

Each cranking signature is some indication of battery status. However, there are some degree of uncertainty and error if only one or two signatures are considered to determine the battery status. By using evidence theory, the evidences (signatures) can be combined to make more accurate and robust decision about battery status.

The evidence theory consists of three processes: basic belief assignment from the individual evidences; evidence combination; and decision making. This section discusses the process and mathematical theory in conjunction with its application to the battery health monitoring problem. The overall structure of the evidence theory based battery health monitoring system is shown in [Figure 1](#).

## METHEMATICAL STRUCTURE

A set of mutually exclusive and exhaustive hypothesis is called a frame of discernment  $\Theta$ . In this paper three hypothesis of 'Good', 'Charge', or 'Replace' of the battery state of health are defined. Therefore the frame of discernment in this case is:

$$\Theta = \{\text{'Good'}, \text{'Charge'}, \text{'Replace'}\} \quad (1)$$

Any subset of  $\Theta$  is also a hypothesis. For example, the subset {Charge, Replace} is interpreted as the hypothesis of "the battery is not good but not sure if we need to charge or to replace the battery." Similarly, the subset {'Good', 'Charge', 'Replace'} means that "the battery state is unknown because

it can be any of the three states.” All subsets of  $\Theta$  are listed in [Table 1](#) with corresponding hypothesis.

## BASIC BELIEF ASSIGNMENT

From each cranking signature (evidence), certain numbers called belief mass are assigned to each hypothesis in [Table 1](#).

**Table 1. Possible Subsets of  $\Theta$**

| Subsets of $\Theta$     | Hypothesis | Belief Mass                           |
|-------------------------|------------|---------------------------------------|
| $\phi$                  | Impossible | $m(\phi) = 0$                         |
| {Replace}               | Replace    | $m(\{\text{Replace}\})$               |
| {Charge}                | Charge     | $m(\{\text{Charge}\})$                |
| {Charge, Replace}       | Not Good   | $m(\{\text{Charge, Replace}\})$       |
| {Good}                  | Good       | $m(\{\text{Good}\})$                  |
| {Good, Replace}         | No Charge  | $m(\{\text{Good, Replace}\})$         |
| {Good, Charge}          | No Replace | $m(\{\text{Good, Charge}\})$          |
| {Good, Charge, Replace} | Unknown    | $m(\{\text{Good, Charge, Replace}\})$ |

The belief mass can be thought to be the level of confidence that the evidence supports each hypothesis. Similar to probability, the belief mass should meet the conditions in [equations \(2\)](#) and [\(3\)](#). Especially the belief mass of empty set should be zero because it cannot happen.

$$m(\phi) = 0 \quad (2)$$

$$\sum_{A \subset \Theta} m(A) = 1 \quad (3)$$

The rule of assigning belief masses from individual evidence (cranking signature) is called basic belief assignment (BBA), and is designed based on the knowledge and experience of each evidence. Once belief masses are assigned, the vector of belief mass as in the third column of [table 1](#) is formed. This vector is called belief vector. The details of BBA rules of individual algorithms are discussed in the later section of this paper.

Each signature has different implication, engineering unit, and scale, and is hardly comparable directly to other signatures. After BBA, however, the information contained in each signature is converted into the same mathematical structure called belief vector, which is more manageable.

## EVIDENCE COMBINATION

Once the cranking signatures (evidences) are converted into belief vectors, the belief vectors can be combined together to form a combined belief vector. This process is called

evidence combination. The central idea of evidence theory is the transformation of a large body of evidence (such as from many sources) into manageable components (belief vector), and combining different pieces of evidence together, by means of combining these components, to get a joint support contribution and at the same time to reduce the uncertainty.  $n$  belief vectors  $m_1, m_2, \dots, m_n$ , given by  $n$  different evidence sources, can be combined by the so-called Dempster's rule of combination in order to make the combined belief vector  $m_c$  as in [Equations \(4\)](#) and [\(5\)](#).

$$m_c(\phi) = 0 \quad (4)$$

and

$$m_c(A) = \frac{\sum_{B \cap C \cap \dots \cap X = A} m_1(B)m_2(C)\dots m_n(X)}{1 - \sum_{B \cap C \cap \dots \cap X = \phi} m_1(B)m_2(C)\dots m_n(X)}, \quad A \neq \phi \quad (5)$$

where  $A, B, C, \dots, X \subset \Theta$ , and  $m_k(A)$  is the belief mass of the belief vector  $m_k$  corresponding to the subset  $A$ .

## DECISION MAKING

Once the belief vectors have been combined, the outcome is combined belief vector  $m_c$ . Now, we have to decide either ‘Replace’, ‘Charge’, or ‘Good’ from the values of the combined belief vector. This process is called decision making. For further discussion let us the introduce concept of belief and plausibility.

$$Bl(A) = \sum_{B \subseteq A} m(B) \quad (6)$$

$$Pl(A) = 1 - Bel(\bar{A}) = \sum_{B \cap A \neq \phi} m(B) \quad (7)$$

$Bl(A)$  indicates amount of belief committed to  $A$  based on the given evidence, while  $Pl(A)$  represents the maximum extent to which the current evidence allows one to believe  $A$ . In evidence theory,  $Bl(A)$  is thought to be the minimum probability that the hypothesis  $A$  is true, the  $Pl(A)$  is thought to be the maximum probability that the hypothesis  $A$  is true. Therefore, the probability  $P(A)$  is in between  $Bl(A)$  and  $Pl(A)$ . From the combined belief vector, we can calculate the belief and plausibility of the subsets {Good}, {Charge}, and {Replace}. For example,

$$Bel(\{\text{Good}\}) = m_c(\{\text{Good}\}) \quad (8)$$