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Online process monitoring with near-zero misdetection for ultrasonic welding of lithium-ion batteries: An integration of univariate and multivariate methods

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ABSTRACT

Ultrasonic metal welding is used for joining lithium-ion batteries of electric vehicles. The monitoring of battery joining processes requires near-zero misdetection in order to prevent any battery joints with a low quality connection going into the downstream assembly. The conventional control chart techniques widely used in many process monitoring systems were designed based on a pre-specified false alarm rate. To ensure weld quality and reduce manual inspection at the same time, a near-zero misdetection rate is desired foremost while achieving a low false alarm rate. A monitoring algorithm targeting near-zero misdetection is developed in this article by integrating univariate control charts and the Mahalanobis distance approach. The proposed algorithm is capable of monitoring non-normal multivariate observations with flexible control limits to achieve a near-zero misdetection rate while keeping a low false alarm rate. By implementing this algorithm on the ultrasonic welding process of battery manufacturing, the developed algorithm proves to be effective in achieving near-zero misdetection in process monitoring to ensure battery weld quality. The developed algorithm also shows great potential for monitoring other processes that target at near-zero misdetection.

1. Introduction

In recent years, increasing concerns over the environmental impact of the petroleum-based transportation infrastructure and soaring gas price have led to great interest in electric vehicles. Electric vehicles require high-power and high-capacity rechargeable batteries. In manufacturing such batteries, significant challenges exist in creating reliable interconnections between battery cells, between modules, and between modules and control units. Such connections must possess reliable electrical conductivity and sufficient mechanical strength to ensure battery performance.

Ultrasonic metal welding is used in joining lithium-ion batteries due to its advantages in joining dissimilar and conductive materials, as discussed by Kim et al. [3]. Ultrasonic metal welding is a solid-state bonding process which uses high frequency ultrasonic energy to generate oscillating shears between two metal sheets clamped under pressure [1]. After removing the surface films and oxides from the surface, the solid-state bond is formed through the plastic deformation of the contacting surfaces under high pressure [4]. As illustrated in Fig. 1, during welding, the transducer transforms electrical energy into high frequency mechanical vibration; this mechanical vibration is transferred to a welding tip through an acoustically tuned horn. This high frequency vibration, applied under force, disperses surface films and oxides, creating a metallurgical bond (Ultraweld® by Branson Ultrasonics Corporation [2]).

The performance of an entire battery pack may not be as desired if any battery joint has a low quality connection. In order to ensure joint quality and not to pass any problematic weld to downstream processes, in a typical battery assembly plant, the quality of every single joint is inspected after the welding process through off-line manual inspection. This leads to delayed detection of low quality welds and a high manual inspection rate. The off-line quality inspection is a complex procedure that requires human operations and considerable time and labor in (a) visual inspection to

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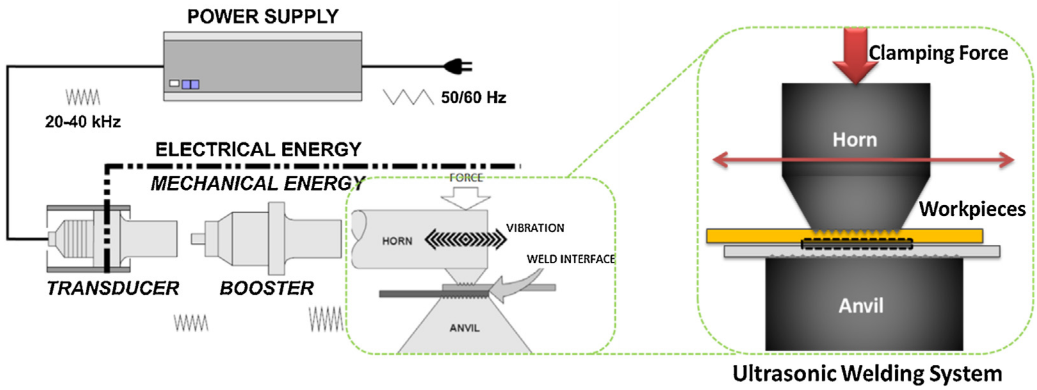

Fig. 1. Ultrasonic welding system [1,2].

ensure the welding spot is at the correct location, and (b) non-destructive mechanical test to ensure the bonding has sufficient strength. The cost of inspection becomes enormous when 100% manual inspection is performed on all welds. Therefore, the battery manufacturing processes used to join battery cells and modules need to be equipped with online real-time quality monitoring and evaluation systems to ensure the quality of joining. This motivates our research to develop an online monitoring system for ultrasonic battery tab welding that can help reduce unnecessary manual inspection rate and ensure the quality of every weld. The monitoring system predicts the quality of each weld based on real-time sensor signals collected from the ultrasonic welding process.

Weld quality has been classified into cold welds, good welds, and over welds by Kim et al. [3] through post-weld studies using the T-peel method. Both cold welds and over welds are considered problematic. Good welds have high peel strengths while problematic welds have low or medium peel strengths. We have observed from lab experiments and plant reports that a normal welding process, although with the presence of inherent variations, usually produces good welds. When the welding process is driven out-of-control due to assignable causes, e.g., metal surface contamination, improperly placed metal sheets, etc., bad welds are generated with a very high probability. For example, when the sheet metal is contaminated with oil (or other substances), the welding power would not ramp up as a normal weld does, thus resulting in a poor quality connection; if the metal sheets are improperly placed between the horn and anvil, the weld spot may fall on the edge of the sheets, also resulting in a poor quality connection; if one of the layers is bend when placing the sheets between the horn and anvil, the original input pressure may not be sufficient to make a strong connection on such an abnormal thickness. Therefore, it is important to detect process changes so that whenever the monitoring system detects an out-of-control sample, it would send a signal alarm to the downstream manual inspection, and the quality of that sample would then be verified by inspection.

Two types of errors may be committed by the monitoring system: false alarm, also known as the Type I error in hypothesis testing, and misdetection, also known as the Type II error. Specifically in this study, the Type I error occurs when the monitoring system announces a battery weld to be a suspect when it is actually in good quality; the Type II error occurs when the monitoring system fails to detect an out-of-control sample that turns out to be problematic. Thus, Type I error from the quality monitoring system results in unnecessary manual inspection efforts. On the other hand, passing a problematic weld will not only potentially impair the performance of the battery pack in electric vehicle, but also harm the performance and safety of the entire vehicle. Hence, Type II error results in passing problematic weld to downstream processes, which is a dangerous consequence that should be avoided. Therefore, the online quality monitoring system for ultrasonic welding of batteries needs to achieve a near-zero Type II error rate foremost while maintaining a relatively low Type I error rate in order to ensure weld quality and reduce manual inspection rate.

Developing a monitoring system for ultrasonic welding of batteries that satisfies the above requirements on Type I and Type II errors is very challenging. The smallest Type I error and the smallest Type II error cannot be achieved at the same time due to the trade-off between risks of getting these two types of errors. When a broader acceptance region is defined, it would reduce false alarms but increase misdetections; on the other hand, a narrower acceptance region reduces the risks of misdetection, but this increases the number of false alarms. The conventional control chart techniques widely used in many process monitoring systems are designed to target a required Type I error rate. In operations where part quality is critical, a near-zero Type II error rate becomes the major goal for the monitoring system. It also needs a low Type I error to reduce unnecessary manual inspections, but even a relatively high Type I error rate (e.g., 50%) represents a substantial reduction in manual inspection. Furthermore, the high frequency and short duration of ultrasonic welding process requires the real-time monitoring algorithm to be computationally efficient and its results to have good interpretability.

The objective of this article is to develop a monitoring algorithm that targets a near-zero Type II error rate foremost while maintaining a relatively low Type I error rate for the online quality monitoring system for ultrasonic welding of batteries. Specifically, the development of such a monitoring algorithm needs to effectively utilize sensor signals and integrate univariate and multivariate statistical process control methods. The developed monitoring algorithm will be used to help ensure part quality and reduce manual inspection costs in battery joining process and other mission-critical manufacturing processes as well. The remainder of this section briefly reviews existing methods on statistical process control. Section 2 describes the data collection procedure and the data and features used in this study. Detailed methodology on the proposed monitoring algorithm is presented in Section 3. Section 4 further demonstrates how the proposed monitoring algorithm works with a case study followed by a discussion in Section 5. Our conclusion is drawn in Section 6.

1.1. Literature review of the related work

In this study, the primary target of the monitoring system is to accurately identify the out-of-control states of the welding process, rather than to distinguish problematic welds that are generated from an in-control process with common-cause variation. The importance of identifying the out-of-control states lies in that out-of-control processes are highly likely to produce problematic