Applying Machine Learning to the Smart Welding of Cylindrical Lithium-ion Battery Cells within Battery Modules

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Abstract

Battery packs are used in transportation and energy storage applications to provide sufficient power for machine operation. There are various types of battery cell structures as well as numerous methods of interconnecting the battery cells. This paper will focus on cylindrical battery cells, the 21700 type, and Smart Welding as the interconnect technology. Smart Welding is a hybrid version of an ultrasonic welder and an ultrasonic heavy wire bonder that was developed by Hesse GmbH. The problem addressed in this study was that previous research pointed to a need for improvement in determining the optimally smart welding parameters for cylindrical lithium-ion battery cells within a module. By using Taguchi techniques and a Naïve Bayes Classifier, a machine learning algorithm was developed to help determine optimum Smart Weld parameters that produced acceptable weld shear values and nuggets.

Key words

Smart Welding, Taguchi techniques, Naïve Bayes Classifier, and weld shear nugget.

I. Introduction

Battery packs are used in transportation and energy storage applications to provide sufficient power for machine operation. Batteries can be at three levels: an individual cell, a module, or a pack. Battery cells are put into an array to form a module, and modules are joined together to form a pack [1]. Lithium-ion (Li-ion) is an emerging chemistry technology in the alternative energy industry due to its low cost, small size, availability, and energy storage capability (Das et al., 2018). Li-ion battery packs are replacing many petroleum-based engines for commercial applications to help reduce pollution since many countries limit combustion engines [2].

There are numerous methods of interconnecting cylindrical cells to a busbar in battery modules. Laser welding, wire bonding, and ultrasonic welding are three common types [3]. Smart Welding is a relatively new technology that is a hybridization of an ultrasonic heavy wire bonder and an ultrasonic welder [4]. Fig. 1 shows a lithium-ion battery module made with Smart Welds between the cylindrical battery cell and a bus bar.

Fig. 1 Smart Welded Battery Module

II. Experimental Design

A. Theoretical Framework

A constructive research study aimed to develop an algorithm for determining optimally smart welding parameters for an aluminum tab to be ultrasonically attached to cylindrical lithium-ion battery cells within a module/pack. Typically, it took months to develop optimal interconnection parameters for battery packs [5], [6], [7]. Companies had to handle massive amounts of test data and used an automated system to expedite the process more efficiently [8].

Upon completion of the actual welding, destructive testing determined the quality of the welds. A visual inspection then determined the weld nugget based on the JEDEC Bond Shear Specification [9]. The shear test was the primary test used to determine the integrity of the ultrasonic smart welds per the JEDEC Standard Wire Bond Shear Test Method JESD22-B116B, Annex B [9].

The theoretical framework employed for finding the optimal weld parameters was Taguchi techniques, a variation of the design of experiments [10]. Ungar and colleagues stated that DoE became a "structured trial-and-error" approach to running experiments and gathering results [7]. Fisher, the statistician who developed DoE, said that if the design of an experiment was "faulty," then interpreting the collected data was "faulty" as well [11].

Taguchi modified the traditional DoE to use as a tool to reduce process variation [10]. Taguchi also believed in other quality philosophy concepts that Fisher did not incorporate into the classic DoE [10]. One example was that Taguchi believed in constant gradual improvements while American companies strive for significant innovations to improve the overall quality [10]. The Taguchi techniques used a fractional factorial approach, called orthogonal arrays, which significantly reduces the number of trials executed than traditional DoE [12]. Another difference was that Taguchi focused on minimizing variance as it utilized the average and variation of the collected data, while DoE only used the average values [12].

The battery cylindrical cell type was 21700. The material for the smart welded tabs onto the cylindrical cells was Al, from Heraeus, which was H14 CR Soft with a tensile strength between 1400 and 2400 cN (CentiNewtons), with an elongation > 10%, and 200 microns thick with a width of 2000 microns.

B. Machine Learning

Machine learning, a subset of artificial intelligence (AI), applied numerical methods to data analysis problems that helped generate new knowledge [13]. Wong briefly summarized machine learning theory, as shown in Figure 2 [14]. The experimental statistical design was used to modify the smart weld parameters strategically. The algorithm is derived from ultrasonic theory, experimental statistical design, descriptive statistical theory, and machine learning.

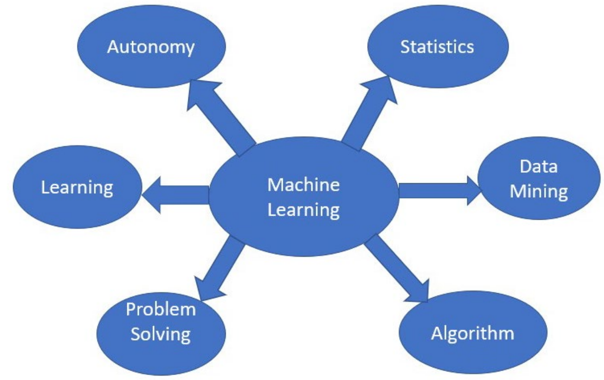

Fig. 2 General Overview of Machine Learning

According to Chapple and Nwanganga, there are two types of machine learning: supervised and unsupervised [13]. Supervised learning, the most common type, utilizes existing database(s) to formulate a model to help predict the labeled data. Labeled data consisted of the values used for the prediction algorithm [13]. With this research, start force, end force, time, and current were labeled data.

Jagan and colleagues defined machine learning as "an artificial intelligence application that gives systems the flexibility to learn and improve through experience mechanically" [15]. Their research involved an intelligent welding process using machine learning techniques. The researchers stated the importance of acceptable welding quality directly impacting a country's economy [15].

Costa and colleagues developed a robotic welding process optimized by machine learning techniques [16]. The researchers took non-integrated process steps of an existing welding operation and used the essential machine learning elements outlined earlier in this chapter to gather information from a sensing device, transfer the data to a software package that did the planning and programming for the welder, and then analyzed that data to get machine learning algorithms developed to enhance weldability [16]. The original welding process that the researchers worked on was a manual type, with the weld quality being based on an Operator's existing knowledge. Costa and colleagues successfully implemented a machine-learning approach that improved the overall weldability of a previous system done manually [16].

C. Test Configuration

The sample size was 206 since it was based on a population of 300, with a 50% variance of the population and a 99% confidence level margin of error [17]. This sample size was appropriate since it was statistically sound for a typical battery module and was in accordance with this research's problem statement, purpose statement, and research question. Due to the limited availability of cylindrical cells, four welds were done on the cells to reach the 206-sample size quantity.

The main machine used was a Hesse Smart Welder, which did the ultrasonic smart welding of the Al tab onto the positive terminal of the cylindrical cells. A 200W transducer was utilized. The cylindrical cell was held rigidly in a fixture on a work holder in the working area of the welder. The cell was held rigidly in the fixture, and the work holder was mounted onto the granite of the smart welder. This was done to ensure no external vibrations interfered with the smart welding process.

The Al was placed onto the positive terminal on the cylindrical cells and held rigidly during the smart welding process. Regarding this research, welding was only done on the positive terminal as the electrolytic nickel plating over the stainless-steel housing was more inconsistent than the electroless plating on the negative terminal.

The smart welds were destructively shear tested on an XYZTec Condor Sigma Bond Tester. The individual cylindrical cells were manually placed on a work holder on the bond tester to ensure the parts under test were rigidly held.

Each smart weld was subjected to a destructive shear test, and that value was recorded in a database within the bond tester. Upon initiating the test, the shear ram descended in Z until a known surface was reached; the shear ram ascended a set distance of 20 microns and then did the shearing of the weld. The researcher visually determined the failure mode of the weld and then scored and recorded it in the bond tester's database. The scoring was per the JEDEC JESD22-B116B [9].

A standard microscope, Leica Model S9, using 10X eyepieces, was used to visually inspect the smart welds by the author.

D. L9 Orthogonal Array Test Results

The testing process was to run the Taguchi L9 Orthogonal Array of 9 trials of strategically modified parameters of start force, end force, time, and current. The transducer was operated in a constant current mode. The smart welding process window was then determined per the destructive shear value and shear nugget based on the JEDEC Bond Shear Standard [shear standard]. The unacceptable smart weld parameters as well as the acceptable smart weld parameters would then be outlined. To then utilize machine learning, the Naïve Bayes Classifier was utilized. Table I displays the Taguchi L9 Orthogonal Array Weld Parameter Settings, and Table II displays the associated statistics and shear nugget quality.

Table I

Taguchi L9 Orthogonal Array Weld Parameter Settings

Trial Group	Current	Start Force	End Force	Time
T1	297	3570	3825	162
T6	350	4500	3825	190
T8	403	4200	3825	190
T7	403	3570	4500	190
T2	297	4200	4200	190
T3	297	4500	4500	219
T4	350	3570	4200	219
T5	350	4200	4500	162
T9	403	4500	4200	162

Table II

Taguchi L9 Statistical and Shear Nugget Quality

Trial Group	Mean	Median	Range	Standard Deviation	Shear Nugget Quality
T1	5.45	5.78	2.58	0.777	Fail
T2	4.15	3.92	3.45	1.177	Fail
T3	4.56	5.06	5.28	1.611	Fail
T4	5.01	5.24	2.92	0.975	Pass
T5	5.46	5.32	1.78	0.529	Pass
T6	4.96	5.09	3.95	1.071	Pass
T7	3.43	3.17	4.45	1.663	Pass
T8	2.26	1.56	5.71	1.739	Pass
T9	3.87	3.85	4.02	1.388	Pass

All Taguchi trial groups had acceptable average shear values. Shear nuggets were reviewed, and trial groups T5 through T9 were found to be acceptable. Trial groups T1, T2, and T3 had unacceptable shear nuggets, but this information was helpful for the Naïve Bayes Classifier segment. Figure 3 shows unacceptable shear nuggets, and Fig. 4 shows acceptable shear nuggets.

Fig. 3 Unacceptable Smart Weld Shear Nuggets

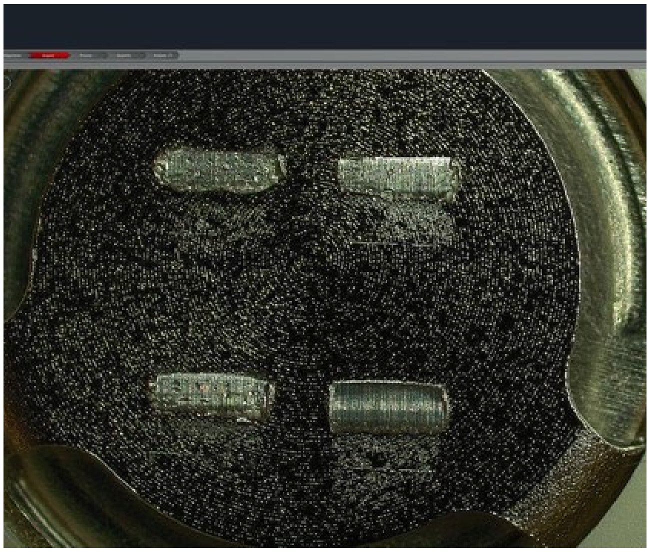

Fig. 4 Acceptable Smart Weld Shear Nuggets

E. Algorithm for Machine Learning

Fig. 5 Algorithm for Machine Learning for Smart Welding

The algorithm developed for this work is listed in Fig. 5. The first step is to run a Taguchi L9 Orthogonal Array on the key variables. The shear test is to be done on the smart welds and a determination of acceptable shear value and/or shear nugget. The next step is to determine if the collection of data samples has acceptable statistics, such as median, average, range, and standard deviation. Some companies prefer the median over the mean. The coefficient of variation is a relationship between the mean and standard deviation. Some companies use this in a production environment with values less than 15% indicating acceptable criteria, and anything above 15% indicates a process not in control.

The weld waveforms show the current and the deformation during the weld time. PiQC is Process integrated Quality Control a patented system from Hesse Mechatronics that monitors 5 variables in real-time to determine how well a weld (or wire bond) is compared to a known entitly [19] source]. The CSV parameters are machine variables (up to 496 variables) obtained from the smart welder on a per-weld basis. One could track particular variables to help with their algorithm. Fig. 6 shows typical smart weld waveforms for deformation (top portion) and current (bottom portion).

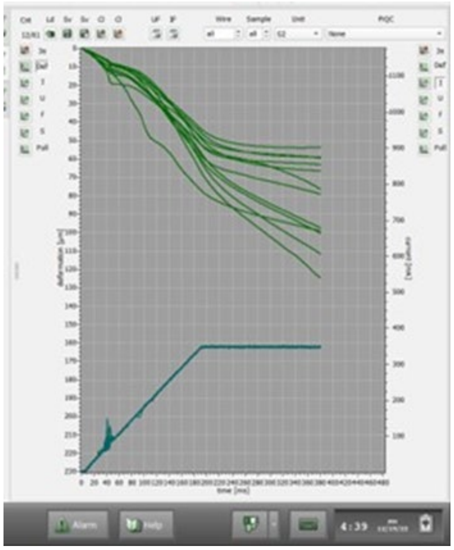

Fig. 6 Smart Weld Waveforms

The next step would be to run the Naïve Bayes Classifier and predict if the new weld parameters would produce an acceptable or unacceptable shear nugget. One would then repeat the algorithm steps to ensure the parameters were feasible or not.

F. Naïve Bayes Classifier

Per Nwanganga and Chapple, "the Naïve Bayes approach is based on the premise that the probability of prior events can be a good estimate of the probability of future events" [13].

The first step was to organize "the Priors." "The Priors" data included the acceptable and unacceptable data. The data was separated into acceptable and unacceptable shear nuggets. The dependent variable was the shear nugget. The independent variables were current, start force, end force, and time. From the Taguchi settings, there was a low, medium, and high value for each of the independent variables. Each independent variable was then classified as a 0 or 1 depending on its state for each of the Taguchi trials. The 0 was for unacceptable shear nuggets and 1 for acceptable shear nuggets. A mapping for the acceptable trials T4-T9 was then done for the Current, Start Force, End Force, and Time for the low, medium, and high parameters. The probabilities for each of the interactions of low, medium, and high values for the acceptable shear values were calculated to be 67%. This was repeated for trails T1-T3 for the unacceptable shear nuggets, and the probability for an unacceptable shear nugget to be produced was 33%. The Naïve Bayes Classifier calculations were done using an embedded function in Excel [18].

Once the mapping for the probabilities was completed, the predictions for acceptable and unacceptable weld parameters based on shear nuggets were determined. The tables for these mappings and predictions were too large for inclusion in this paper.

New parameter sets labeled Algorithm 1 through Algorithm 6 were developed using parameters in the range of low, medium, and high values to test if the predictions were correct or incorrect. These new parameters are listed in Table III.

Table III

New Parameter Trials to Test the Predictions

Algorithm	Current	Start Force	End Force	Time
1	310 (L)	3570 (L)	3825 (L)	200 (H)
2	305 (L)	3570 (L)	3825 (L)	195 (M)
3	375 (M)	4200 (M)	4500 (H)	175 (L)
4	375 (M)	3700 (L)	3825 (L)	162 (L)
5	395 (H)	4500 (H)	3825 (L)	162 L
6	395 (H)	4500 (H)	4500 (H)	219 (H)

The result was that the shear nuggets aligned with the predictions. Algorithms 1, 2, and 3 yielded unacceptable shear nuggets, and algorithms 4-6 had acceptable shear nuggets.

III. Conclusion

The algorithm for this research was successfully functional. The first segment of the algorithm was to develop the various welding parameters using a Taguchi technique. Those nine trials produced welds that were analyzed and evaluated for shear nuggets. That data was then applied to a Naïve Bayes Classifier, where predictions were made on what parameters could make unacceptable and acceptable shear nuggets. New parameters were input into new Taguchi trials, and those welds were evaluated, and the predictions matched the observed sheared nuggets.

The author determined that using shear value was not as important as shear nuggets because numerous high-value shears had unacceptable nuggets.

The author understands there are numerous methods of running experiments, but historically, the Taguchi L9 Orthogonal Array has been shown to produce significant results in less amount of time than a full factorial experimental design.

Future work will involve ramping the current, determining a method of measuring the expected shear nugget without using the external shear test, and to incorporate R or Python to help include huge amounts of data from other CSV variables to enhance the machine learning algorithm.

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