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Implementation Strategy for Launch and Performance Improvement of High Throughput Manufacturing Inspection Systems

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Abstract

Product technologies are changing rapidly in advanced automotive propulsion systems. These products are driving the need for new manufacturing processes and new inspection methods. To keep new propulsion systems affordable and ensure these new products are introduced with high quality, automotive manufacturers are seeking automated inspection solutions with low cost and near-zero error rates to inspect 100% of the items. In this paper, a progressive deployment strategy of a hybrid inspection system is presented and studied in the context of technology development and rapid deployment. It enabled us to begin with human inspection and gradually phase-in automated inspection technology, while almost never failing to identify a bad item. This strategy was applied successfully to inspect ultrasonic welds in lithium ion battery packs. At the time of this study, a 75% reduction in human inspection was achieved with prospects for further reduction. Actual results from the implementation of this strategy in production are presented. Recommendations are made regarding the most appropriate time to employ this strategy and how it could increase the use of advanced automated in-line inspection technologies.

Keywords: Hybrid Inspection; Human Inspection; Automated Inspection; Battery Assembly; Ultrasonic Welding; Chevrolet Volt

1. Introduction

Automotive products and processes have been changing rapidly. These changes include advances in pure battery-electric systems, hybrid-electric, fuel cells, ex-fuel engines, clean diesel, and compressed natural gas, to name a few. These new products have come with many new manufacturing challenges which are driving the need for new advanced manufacturing processes and associated inspection methods. To keep costs down and ensure these new technologies are introduced with high quality, automotive manufacturers require low-cost automated inspection solutions with near-zero Type I (false alarm) and Type II (false acceptance) error rates. This is consistent with the trend towards Zero Defect Manufacturing (ZDM) [1]. However, since the product and manufacturing processes are new, reliable automated inspection solutions often do not exist. In such cases, manufacturers must rely on manual inspection methods until new automated methods are developed. Depending on the application [2, 3], it may take several years until a viable automated solution is ready for production implementation.

Manual inspection has important strategic advantages and limitations when compared to automated systems. Manual inspection systems require little investment to implement. Humans are highly exible and adaptable to changes [4]. Human inspectors are generally better at classifying observable defects [2, 3] as acceptable or not [5–7]. Therefore, manual inspection can be employed rapidly and can be used to respond to any urgent need for quality inspection. However, manual inspection drives additional labor expense. It also may have less consistent performance (i.e., error rates) due to several factors including: differences between inspectors, the time allotted for

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inspection, training, vigilance decrement, the probability of a defect occurring, and others [8–10].

Increasing levels of automation and computerization and artificial intelligence allow manufacturers to employ automated in-line inspection technologies for quality verification. Automated systems have several benefits including reducing labor costs, providing more consistent performance over time, and improved performance in searching to identify possible defects [5–7]. In our experience, automation also drives higher investment costs and requires substantial development and implementation time for new inspection tasks. Table 1 provides a comparison of selected attributes of fully manual in comparison with fully automated inspection technologies. Other more comprehensive taxonomies and comparisons between manual and automated inspection technologies can be found in [11, 12].

Table 1. Selected characteristics of manual and automated inspection.

Characteristics	Manual Inspection	Automated Inspection
Cost	Low capital, high labor	High capital, low labor
Flexibility	High	Low
Overall performance	Varies by operator, affected by fatigue/ boredom	Consistent performance and error rates
Potential defect identification	May overlook some potential defects	More consistent identification of potential defects
Defect classification accuracy	Generally, will have Fewer false alarms	May result in more false alarms
Technology development	Little or no development time	Requires more development time
Maintenance	Low complexity and maintenance	Higher complexity and maintenance
Data recording	Less data; might include errors	More data with greater accuracy
Problem solving	Humans can problem solve and make associations with other events	Not able to solve unforeseen problems
Ergonomics	Potential concerns with repetitive motion disorders and eye strain	No ergonomic concerns
Artificial Intelligence readiness	Low	High

In the automotive industry, business decisions and strategy around inspection technology have been conservative. Traditionally, manual inspection and automated inspection have been considered mutually exclusive. One is a substitute for another, "winner-take-all". If automated systems with mature technology will operate with lower cost, higher throughput, and lower error rates than humans, manufacturers seek to replace manual inspection with automated inspection [13]. Up until that point of maturity, automated inspection systems are typically not implemented. Unfortunately, it takes a long time to develop new automated inspection technology to the required level of maturity needed to replace manual inspection. Although the winner-take-all strategy is reasonable regarding managing the introduction of new inspection technology, we have found that it may be overly conservative. It does not allow a manufacturer to realize any benefit from less mature automated technologies which can take on at least a portion of the inspection workload. Furthermore, this strategy may result in a failure to implement new automated inspection capabilities if the performance requirement cannot be met in time.

In our case, we were presented with a challenging time constraint as we were developing a new battery tab weld inspection technology. In response, we devised a new progressive deployment strategy utilizing a hybrid inspection configuration [7, 9, 14–17] that allowed the manufacturing plant to benefit from even partially performing automated inspection technology [18] in time. The benefit of this strategy then increased over time as the inspection technology was improved through learning while in a production setting.

Implementation of our progressive deployment strategy began with 100% manual inspection. We then introduced the new automated inspection strategy, albeit at its infancy, in a tandem configuration with a manual inspection system. In this tandem configuration, the goal of the automated system is to reduce the defect search space for the human inspector by screening the obviously good items. The manual classifier would then focus on the not good, or "suspect" pool of items and classify them into good and bad. This approach reduced the overall workload on the operation and allowed a longer inspection time that could drive up the accuracy of the human inspector. The hybrid inspection system also allowed automated inspection to be introduced sooner with low risk, even when the technology was not mature enough to stand on it's own. Additionally, the automated system could learn faster from the manual inspection results on real manufacturing data. In the progressive deployment strategy, if and when the automated system reached a maturity level to match or beat the manual inspection system, the automated system could be used to replace the manual one.

Our progressive deployment strategy was closely aligned with the concept of ZDM, where the goal was to dramatically improve the robustness of manufacturing processes through data driven methodologies [19]. The ultimate objective of ZDM was to not produce any products that did not fall within engineering specifications. Azamfirei et. al. [1] and Psarromatis et. al. [19] provided insights and comparisons of ZDM approaches through state of the art surveys using advanced bibliometric analysis. Each study examined literature using similar search phrases and different but overlapping periods of time (1987–2018, and 2011–2022, respectively). It is important to note that, in spite of the overlap in search terms and time period the results were quite different. Among the nearly 500 papers analyzed in both studies there were only four in common. The study in [1] spanned the more recent time period from 2011–

2022 with slightly less than half of the papers published in the first eight years and the remaining papers published in 2019–2022. We believed this was due to an increased interest in the general topic and better understanding of where and why to implement such methodologies.

Both [1] and [19] classified inspection systems along the dimensions or strategies of predict, detect, prevent, and repair. Azamfirei et. al. classified "detect" and "predict" as triggering strategies, while "prevent" and "repair" were action strategies. Our approach was aligned with this philosophy. However, the lines between "detect" and "predict" were blurred in and Industry 4.0 implementation. Both required data streams to operate and while one might be a direct observation while the other was an inference, both had the same effect.

Hybrid inspection methods have been used for a number of years as a means to improve overall reliability [7, 9, 14–17]. For faster implementation of our inspection technology, we implemented a special case of hybrid inspection, namely a cascading approach of an automated "predict-prevent" system used to identify components that need further inspection, and then a manual "detect-prevent" inspection step to interrogate this reduced set of components.

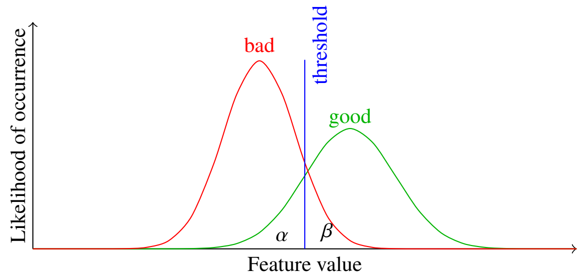
Upon review of available literature, we believe that using this progressive strategy for hybrid inspection technology deployment and improvement is relatively new and unique, and therefore warrants further analysis and study. We identified prior work such as [19], which pointed to utilizing input from human inspectors to improve system classification performance. However, a recent literature survey of 145 articles on ZDM from 2011 to 2022 [1] did not mention the concept of employing hybrid inspection systems to improve inspection performance and to speed the development and implementation of new inspection technology. Furthermore, although technology learning concepts that differentiated the benefits of learning-by-research and learning-by-doing have been described in literature related to energy technology innovation [20–22] and enterprise resource planning implementation [23, 24], we did not find, outside of our work, that these concepts have found their way into manufacturing inspection system technology deployment.

In this paper, we introduce our approach of progressive deployment of a hybrid inspection system which was motivated by the philosophy of process monitoring for quality [18]. In Section 2 we introduce the general understanding of inspection system performance from the perspective of error analysis. Then, we contrast the manual/automated inspection system with the hybrid inspection system. We also show how the error behavior progresses in the hybrid system. The focus of Section 3 is deployment strategy. We describe the winner-take-all strategy and our progressive deployment strategy, and discuss the benefits of using the latter with the help of some mathematical models. Finally in Section 4 we include results from a real manufacturing process where we used the progressive deployment strategy. Section 5 contains our concluding remarks.

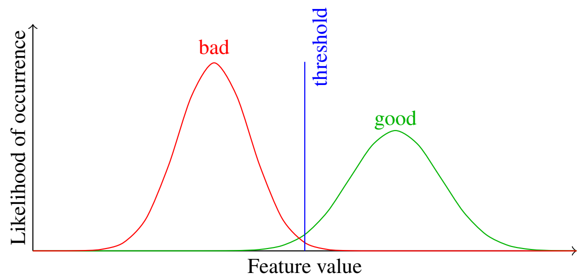
2. Inspection Systems

Choosing an inspection system is largely governed by characteristics of the errors observed by the classification. In a binary classification task where items are being labeled as two classes, "good" or "bad", there are two kinds of errors rates, α and β (α, β $[0, 1]$) [25]. The α error rate, also known as the Type I error rate, is the rate of falsely rejecting a good item thinking it is bad. The β error rate, also known as Type II error rate, is the rate of falsely accepting a bad item thinking it is good. While no inspection system can be error free, the chosen one optimizes these errors depending on business objectives.

The two errors are not independent. Minimizing one might come at the expense of increasing the other. Consider a manufacturing process where good and bad items are made and an aspect of the item (a feature), could be color, or dimension, is being monitored for quality inspection. The feature of the good items, in this example, are normally distributed with a certain mean and variance, and that of the bad items are also normally distributed but with different mean and variance, as shown in Figure 1(a). In this illustration, any item with its feature value



(a) Classes with significant overlap.



(b) Classes with significant separation.

Figure 1. Features from good and bad items as two normal distributions.

below a certain threshold is considered bad. Note that there is a certain probability of making good items that can fall below the threshold. Those items get wrongly classified as bad and the probability of that happening is α. Similarly, bad items can have feature values that are beyond the threshold, which will lead to accepting them as good items. The probability of that happening is β. When these error rates are not acceptable, we can choose to monitor a different feature such that the separation of the two distributions is increased as shown in Figure 1(b), reducing both errors. When such a feature is not available/observable, we can adjust our threshold to reduce one er-

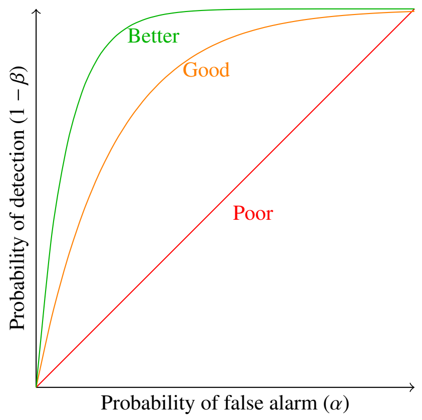


Figure 2. Receiver operating characteristics.

ror, often the one that costs more, at the expense of the other in order to reduce our overall cost of making errors.

The performance of an inspection system can be summarized in a receiver operating characteristic (ROC) curve [25] as shown in Figure 2. In the figure, there are three ROC curves, corresponding to three different classifiers. Each ROC curve denotes the performance of a classifier by plotting α versus $1-\beta$ for all possible threshold values. Each point on a ROC curve correspond to a specific threshold. Given a classifier, one can determine the error tradeoff from an ROC curve. A simultaneous reduction of both errors is only possible by improving the classifier, by changing the classification rule and/or the feature being monitored.

A confusion matrix could be used to summarize the errors for an inspection system deployed in a manufacturing process making n items of which n_g are good and n_b are bad, i.e. $n = n_g + n_b$. It can be used to summarize the outcome of an inspection, as shown in Table 2. To calculate the probability of

Table 2. Confusion matrix.

true | classified	"Good"	"Bad"	Row Total
Good	$\hat{n}_{g\,g}$	$\hat{n}_{b\,g}$	$n_g = \hat{n}_{g\,g} + \hat{n}_{b\,g}$
Bad	$\hat{n}_{g\,b}$	$\hat{n}_{b\,b}$	$n_b = \hat{n}_{b\,b} + \hat{n}_{g\,b}$
Column total	$\hat{n}_g = \hat{n}_{g\,g} + \hat{n}_{g\,b}$	$\hat{n}_b = \hat{n}_{b\,g} + \hat{n}_{b\,b}$	$n = n_g + n_b = \hat{n}_g + \hat{n}_b$

errors, the row labeled "Good" needs to be normalized by n_g and the row labeled "Bad" needs to be normalized by n_b. Finally, the confusion matrix may be row-scaled and expressed in terms of the error performance as shown in Table 3. In an ideal

Table 3. Row-scaled confusion matrix.

true | classified	"Good"	"Bad"
Good	$(1-\alpha) = \dfrac{\hat{n}_{g\,g}}{n_g}$	$\alpha = \dfrac{\hat{n}_{b\,g}}{n_g}$
Bad	$\beta = \dfrac{\hat{n}_{g\,b}}{n_b}$	$(1-\beta) = \dfrac{\hat{n}_{b\,b}}{n_b}$

scenario, with $\alpha = \beta = 0$, the row-scaled confusion matrix would be an identity matrix.

2.1. Traditional Inspection System

In a traditional inspection system, an item is inspected either by a human operator or a machine. In a manufacturing framework, such an inspection system produces a work ow as shown in Figure 3. If a manual inspection system is uti-

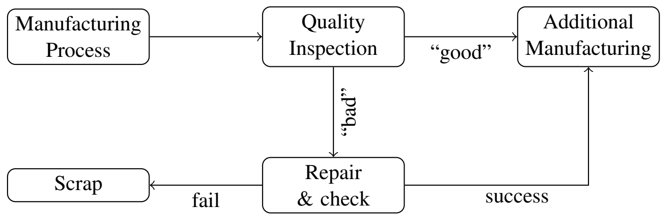


Figure 3. Traditional inspection system.

lized, the complete "quality inspection" function would be performed by human inspectors and the features used must be human observable. The corresponding error rates are α_M and β_M. In an automated inspection system, the complete "quality inspection" function is performed by a computer system. It could use directly observable features or their surrogates as described in [2, 18]. The automated inspection system might deploy several different classifiers in an ensemble with final decision error rates of α_A and β_A.

2.2. Hybrid Inspection System

A hybrid inspection system combines automated inspection technology with human inspection to achieve improved inspection performance [7, 9, 14–17]. A hybrid inspection system could be based on a two part pass/fail classification where the the first classifier uses an automated process to screen the "good" from the "suspect" and the second test, the manual test, scrutinizes the "suspect" to come to a final pass/fail decision as shown in Figure 4. The decision process and associated prob-

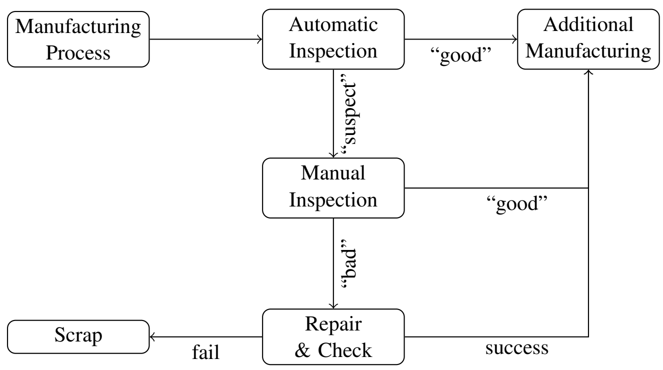


Figure 4. Hybrid inspection system.

abilities that underlie the counts in a confusion matrix can be shown in a probability tree. Figure 5 shows a probability tree for a hybrid inspection system. The probability tree consists of

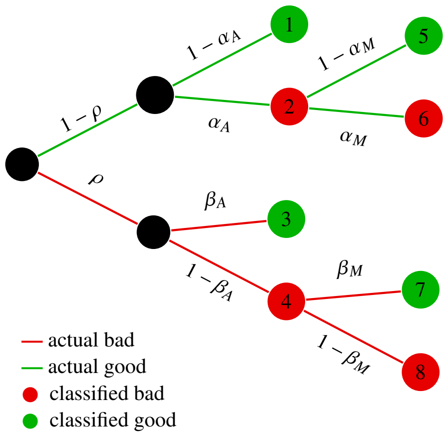


Figure 5. Probability tree for a hybrid inspection system.

segments and nodes. The initial node (on the left) indicates the creation of the item that is good with probability $1-\rho$ and bad with probability ρ. When a good item is inspected using an automatic method, the probability that it is classified as "good" is $(1-\rho)(1-\alpha_A)$. This value is associated with node 1 in the Figure and contributes to the $\hat{n}_{g\,g}$ cell in the confusion matrix in Table 3. Nodes 1, 2, 3, and 4 contribute directly to the confusion matrix in Table 4. The probability at each terminal node

Table 4. Confusion matrix for first part, automated classification.

true | classified	"Good"	"Bad"
Good	$n(1-\rho)(1-\alpha_A)$	$n(1-\rho)\alpha_A$
Bad	$n\rho\beta_A$	$n\rho(1-\beta_A)$

is the product of the probabilities that are associated with each segment that constitutes its path. In the context of the hybrid inspection system, the items that would be called "bad" in a traditional classification (nodes 2 and 4) are called "suspect" after the first part. Nodes 1, 5, 6, 3, 7 and 8 contribute to the hybrid classification whose confusion matrix is given in Table 5. Normalization of this table results in the final row-scaled confusion matrix with the error rates for the hybrid inspection system as shown in Table 6, where α_H and β_H are the error rates for the hybrid inspection system. Examining the row-scaled confusion matrix, we can draw the following conclusions.

Table 5. Confusion matrix for hybrid classification.

true | classified	"Good"	"Bad"
Good	$n(1-\rho)(1-\alpha_A\alpha_M)$	$n(1-\rho)\alpha_A\alpha_M$
Bad	$n\rho(\beta_A+\beta_M-\beta_A\beta_M)$	$n\rho(1-\beta_A)(1-\beta_M)$

- The α-error rate for the hybrid system is no worse than either system when used traditionally, i.e. $\alpha_H \leq \alpha_A$ and $\alpha_H \leq \alpha_M$.

Table 6. Confusion matrix for hybrid classification.

true | classified	"Good"	"Bad"
Good	$1-\alpha_H = 1-\alpha_A\alpha_M$	$\alpha_H = \alpha_A\alpha_M$
Bad	$\beta_H = \beta_A+\beta_M-\beta_A\beta_M$	$1-\beta_H = (1-\beta_A)(1-\beta_M)$

- The β-error rate of the hybrid system is no better than either system when used traditionally, i.e. $\beta_H \geq \beta_A$ and $\beta_H \geq \beta_M$.
- An improvement in the manufacturing process by reducing ρ would reduce the overall count in the errors.
- The hybrid inspection system reduces the manual inspection by a factor of $((1-\rho)\alpha_A + \rho(1-\beta_A))$.

3. Deployment Strategy

3.1. Winner-take-all Deployment Strategy

The traditional deployment strategy for new inspection technology is winner-take-all. There are only two possible systems that are implemented as solutions. The deployment would start with a manual inspection system and utilize data gathered from that system to support the building and benchmarking of a new automated system. In parallel, a research and development project would attempt to develop an automated inspection system that could outperform the manual one. Once the automated system is developed to the point where it could outperform the manual one, it is implemented as a replacement. Otherwise, the manual system remains. The ow of this logic is shown in Figure 6. In practice, development of an all-new automated inspection system might require years of development until it could outperform a human inspector. Therefore, in this "winner-take-all" approach, the automated system might never be mature enough to replace the manual method during the limited life of a specific product line for which it was being developed. Even if the automated technology could provide some useful information, the winner-take-all implementation strategy provides no means to derive benefit from it. This might result in wasted research and development effort and missed opportunity.

3.2. Progressive Deployment Strategy

Our deployment approach provides a means to gradually introduce a new automated system, as shown in Figure 7. We started production with the manual system and utilized the inspection results to build and benchmark the automated system. The cost of missing a bad weld was tremendous, from a product quality, warranty cost, and customer satisfaction perspective. Hence, our objective was to design a system with $\beta_A = 0$. Any classifier could achieve $\beta = 0$ if $\alpha = 1$. In order to limit α, we set an upper threshold $\hat{\alpha}_A$. Once $\alpha_A < \hat{\alpha}_A$ was satisfied, we could insert the automated inspection system in tandem with manual

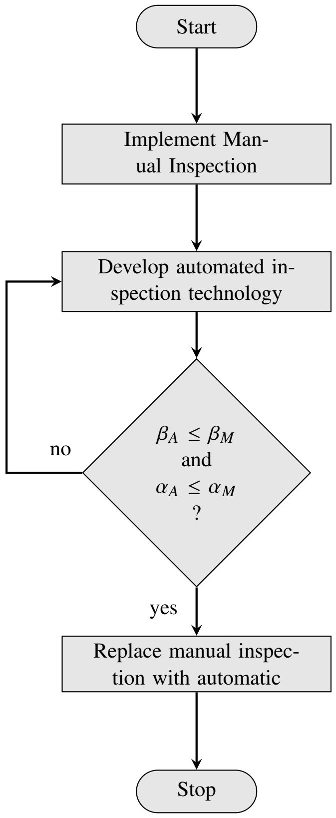


Figure 6. Winner-take-all deployment strategy.

inspection, creating the hybrid inspection system as shown in Figure 4. During the time the hybrid system was operational, its α-error rate was monitored with the objective of error reduction. If α_A would have fallen below a certain acceptable error limit of α_A^*, the manual system could have been removed and the automated system could have taken over. In other words, the hybrid system operates with $\beta_A = 0$ and $\alpha_A^* \leq \alpha_A \leq \hat{\alpha}_A$.

3.3. Bene ts

The hybrid inspection system enables the progressive deployment strategy. Progressive deployment allows for early insertion of automated inspection systems in production and then allows a risk-free trial period during which the automated system could be incrementally improved.

While automated systems rely on a large volume of training data, it is also essential that the chosen system has the ability to converge. In other words, the correct classifier rule(s) and the discriminating features have been chosen [18]. The choice of this is performed by humans, and humans have a technology learning curve [26–28] which can be represented by a power law

$$\alpha_A[m] = \alpha_A[1](m)^{-x},$$

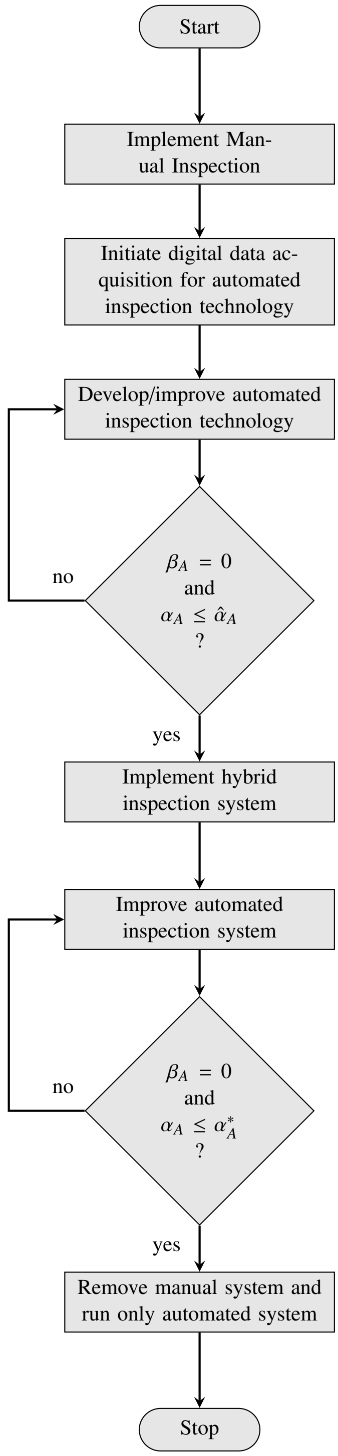


Figure 7. Progressive deployment strategy.

according to [26, 27]. Here, $\alpha_A[m]$ is the α-error rate after inspecting $m \leq n$ items and x is the learning rate parameter. One could think of m as an epoch and with every passing epoch there is more data to train on and more experience for the people developing the system.

While improvements are made to the automated system, the human inspector simply inspects a few less welds as concluded in Section 2.2. Given a target takt time T for the manufacturing line, the allotted time for inspecting each weld by n_i inspectors is,

$$t = \frac{n_i T}{n}\left(\frac{1}{(1-\rho)\alpha_A + \rho(1-\beta_A)}\right) = \frac{n_i T}{n\gamma}$$

The reduction factor in welds to inspect $\gamma = (1-\rho)\alpha_A + \rho(1-\beta_A)$ is obtained from Table 4. With decreasing α_A, the inspector(s) have more time to carefully inspect the weld.

Experiments on test error rates in manual inspection have determined that test error rates can be impacted by several factors including differences between inspectors, the time allotted for inspection, training, vigilance decrement, the probability of a defect occurring, and others [8–10]. However, one of the most important and quantifiable factors is the time allotted for inspection [4, 10]. More specifically, the probability of detection is very sensitive to time limitations, and external pacing of inspection task might increase errors [8]. Likewise, the probability of detecting a defect increases as the time to inspect increases [4] within a range. In manufacturing operations where inspection times are brief (e.g., less than one minute) and external pacing is utilized. This impacts the accuracy of the inspection. Probability of detecting a defect (P_d) is related exponentially to allotted time t in an overall inspection task [4, 29] and can be modeled as

$$P_d = 1 - \exp\left(-\frac{t}{\bar{t}}\right),$$

or

$$P_d = 1 - \left(k - \frac{\exp(yt)}{1+\exp(yt)}\right)$$

where $\bar{t}$, k and y are modeling parameters. Allowing more time t to inspect therefore increases the probability of detection of defects.

In addition, with a sufficient increase in t that could be driving P_d 1, it provides an opportunity to reduce n_i from this task. Every bit of error reduction would result in benefits including labor efficiency gains, improved reliability of the inspection system, and a reduction in ergonomic concerns. In addition, electronic data collected routinely from the automated system and classified by the human inspector contributes to training the automated system. System data was also analyzed to identify opportunities for weld process improvements. Analyses include root cause identification for defect reduction, weld process variation reduction, and tool life analysis. Without the hybrid system, this data would not have been available.

On the other hand, the worst case scenario could lead to $\alpha_A \approx 1$, implying γ 1, which would be similar to 100% manual inspection.

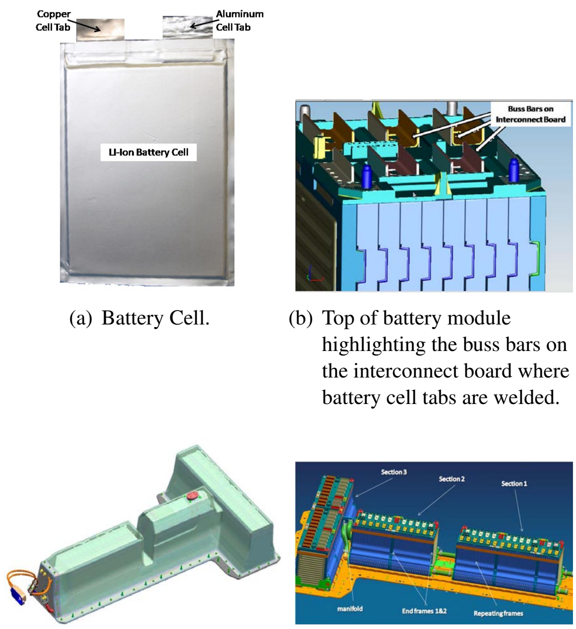
The impact of the hybrid system form an overall production quality was significant. In Table 6 we establish the relationship of of the errors of the hybrid system with the individual systems.

$$\alpha_H = \alpha_A \alpha_M$$
$$\beta_H = \beta_A + \beta_M - \beta_A \beta_M$$

The α error obviously was reduced by cascading the two systems. In fact, the human inspectors were trained for α_M 0, resulting in $\alpha_H \approx 0$. The automated system was tuned for $\beta_A = 0$, resulting in $\beta_H = \beta_M$. The excess allowed time and the well designed interface enabled β_M 0.

4. Case Study

The problem at hand was to inspect ultrasonically welded battery tabs of Li-ion battery pack used in a vehicle [18]. Each battery pack had 192 ultrasonic welds that were necessary for joining battery cells to the buss bars on the interconnect boards (Figure 8). Each cell tab had one copper tab and one aluminum



(a) Battery Cell.
(b) Top of battery module highlighting the buss bars on the interconnect board where battery cell tabs are welded.
(c) Battery pack with cover.
(d) Battery pack without cover.

Figure 8. Views of Li-ion battery pack.

tab. Half of the welds in the battery pack joined copper cell tabs to the copper buss bar and the other half joined aluminum cell tabs to the copper buss bar. Since the tab connections created an electrical series circuit, every single weld had to be good for the pack to work. Therefore, it was determined that 100% in-line inspection was necessary. Unfortunately, less than one year prior to the start of regular production, the only viable method of inspecting these joints was manual inspection. To avoid the expected high costs, and ergonomic impacts stemming from the manual inspection of millions of welds per year, efforts began in earnest to invent a 100% in-line automated system for verifying ultrasonic weld joint quality.

After one year of intense development effort, a promising prototype system based on a novel classification algorithm and novel features [30–33] was ready for plant trial. The hardware and initial software were put in place prior to start of production. However, the data needed to train the system and verify the system's performance was limited to a relatively small sample of laboratory data. The defect rate of the process was extremely low ($\rho \approx 0.15\%$), making it necessary to collect data for months of production to train the system. Production had to begin with manual inspection. The plant could sustain a gradual ramp up to full production rate over a period of seven months. It was empirically determined during this period that the production defect rate of copper welds was almost zero, $\rho_{\mathrm{Cu}} \approx 0$. So, we needed a system to verify the Aluminum welds with $\rho_{\mathrm{Al}} \approx 0.002$.

The specification for the inspection system was to have low α, but $\beta = 0$. The cost of missing a bad weld was very high. Despite training using the available data the error rate requirement was not achieved.

The manufacturing committee decided that $\hat{\alpha}_A = 0.5$ would be a good insertion point for the automated system. It would at least cut the manual inspection by half. We observed, modified, and retrained the system for the first few months, and once we achieved $\alpha_A \approx 0.5$, we switched from 100% manual to the hybrid mode. Figure 9 shows the errors that the automated system generated at this initial phase. Once implemented, we observed

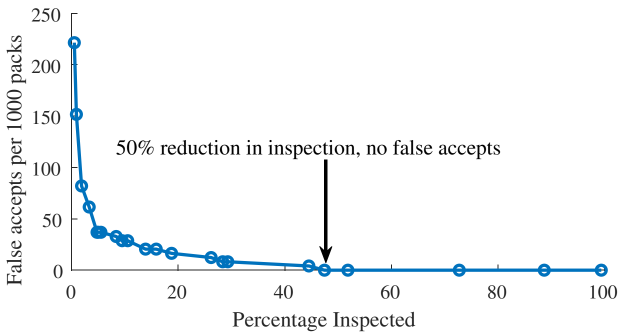


Figure 9. First release of automated inspection system for ultrasonically welded battery tab joints.

a general decay trend in the α_A from all the stations as shown in Figure 10. This was in alignment with the expectations from the power law for technology learning in Section 3.3.

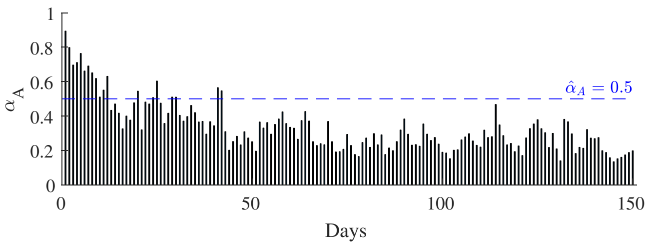


Figure 10. Daily α_A, or rate of "suspects" for first 150 days.

During this period, there was progressively more data available to design and train the classifiers. We utilized all available data, a growing set, to design and train classifiers. The decay trend was a compound effect of human and machine learning.

The authors in [4] specified that the errors in detection is impacted by discriminability of the defect. In our scenario, the inspectors would pick at the weld to ensure adhesion.

The only other source of error that we observed, was in transferring the result of the human inspection system to the computer. At first, the implementation was not ideal for the human inspector, because the numerous "suspect" welds were in random positions. A screen with the "suspect" weld locations were presented, as shown in Figure 11(a). It was challenging for a human inspector to determine these positions, inspect it, and report the quality back to the computer system. In addition, the

(a) Initial display for presenting "suspect" weld positions to the human inspector. "suspect" welds are highlighted in red color.

(b) Projected light on battery section highlights "suspect" welds for manual inspection.

Figure 11. Tools to enhance human inspection performance.

automated system would occasionally have $\alpha_A > 0.5$ due to non-stationarity of the process or other unpredicted changes in the manufacturing process. At that point, it was just faster to inspect all the welds.

Two months later, a novel projection system [11, 34, 35] was implemented which directly illuminated the "suspect" weld positions on a battery module with projected light. Figure 11(b) shows how the "suspect" welds were indicated by a brighter yellow light. This interface eliminated the need for the human inspector to correlate the weld from the screen to the physical module by having to manually count and determine it's location. As the automated system evolved progressively through more days where α_A reached 30% or less, the benefit of the hybrid system became apparent. Towards the end, the human inspector had to only intermittently inspect some welds.

5. Conclusion

In this paper, a progressive deployment strategy of a hybrid inspection system has been described that was used to inspect 100% of all ultrasonic welds used to connect cell tabs to buss bars in a Li-ion battery pack. This strategy enabled us to begin with manual inspection and gradually phase-in automated inspection technology. The strategy began with start of production using 100% manual inspection. While the inspection was manual, the digital record keeping enabled the development of an automated inspection system. The automated system was designed to miss no bad items and screen out the obviously good ones. The remaining suspect items were sent for manual inspection. This reduced the manual search space for an inspector and allowed a longer inspection time. Once the automated system could screen out at least half of the items without mistakes, it was introduced in the hybrid framework. This approach enabled accelerated deployment of new automated inspection technology and both the systems could benefit from each other.

The mathematical formulation of error trend and human proficiency models has helped us understand the benefits of the system and indicated where improvement could be made. Cascading of the automated system reduced initial errors. One might have thought that the combination of it with the manual system could increase missed defects, but a combined final understanding of the hybrid system demonstrated that the system could actually function at almost zero-error.

After one year of maturity, we observed in our manufacturing facility that we could reduce manual inspection by over 75% without compromising inspection quality. The results of the actual implementation demonstrated that the hybrid approach enabled a rapid introduction of automated technology which significantly improved the labor efficiency of the manual inspection and minimized the chances for ergonomic concerns. It has also improved the reliability and consistency of the inspection process by reducing the search space for the human inspector. In addition, the hybrid approach and the enhancements in the human machine interface that it required, was an important enabler for process improvements because of the capability to collect large amounts of detailed, well curated process data that could be analyzed for improvements.

After five years of deployment and investigation in the topic of non-destructive evaluation of ultrasonic welds, we realized that it would have taken us years and lost opportunity if we decided to perfect the automated system before deploying it.

Ultimately, decisions around the right inspection strategy must consider economics and risk tolerance. For example, the additional investment cost of the automated system must be weighed against expected cost savings due to labor efficiency gains and reduced inspection error rates for human inspectors. Also, when determining acceptable error rates, one must consider the cost of bad parts being delivered to customers and the cost of interrupting production with false alarms. The technology development cost and improvement rate in the automated inspection system should also be considered through a learning analysis before a full assessment of the economics can be made. Future work should include a comprehensive cost model which appropriately balances economics, quality risks, and technology learning.

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