

Manufacturing management approach with AI and statistical methods for improvement of Printed Circuit Boards manufacturing quality

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With the advancement of electric vehicles and automated driving, customers are demanding higher functional performance as well as longer driving times, with the vehicle increasingly regarded as a personal space. As a result, not only are a wider variety of electronic components being installed, but the operating conditions and environments for these components are becoming more severe than ever, leading to greater diversity in printed circuit board designs and circuit structures. Consequently, as vehicle electrification progresses, the importance of manufacturing quality for printed circuit board is increasing day by day. However, current challenges include quality variations arising from the large number of printed circuit board suppliers, as well as the inherent difficulty of process control in wet processes used in printed circuit board fabrication.

To address these issues, this study proposes a manufacturing control approach that leverages AI and statistical methods to improve printed circuit board manufacturing quality. The proposed approach combines (1) AI-based learning on historical data and (2) real-time construction of estimated distributions using Bayes' theorem. In the AI-based learning of historical product data, the characteristics and trends of both in-process defective boards and field-failure boards are extracted and clarified. For real-time distribution estimation, posterior probabilities are calculated by applying Bayes' theorem, and the degree of similarity to historical data distributions is quantified. An estimated distribution is then constructed by weighting historical distributions with these posterior probabilities. This enables real-time creation and updating of control distributions without waiting for completion of the entire production lot, in contrast to conventional practice where distributions are only constructed after lot completion.

For theoretical verification of the proposed method, dummy datasets were created to represent historical data and in-process production data, and verification was performed. The results confirmed that AI can successfully extract characteristic features from past data. With respect to the estimated distributions, it was shown that even with a small number of data points at the early stage of production, it is possible to construct an estimated distribution that reflects past data. Moreover, by modeling the estimated distribution as a mixture distribution whose components are weighted by the posterior probabilities of each historical dataset, the method can generate an estimated distribution based not only on the tendencies of a particular dataset but on all historical data, even under conditions where the number of samples is small. In addition, for multi-stage processes, by substituting the posterior probability from an upstream process as the prior in Bayes' theorem for the downstream process and incorporating the covariance between processes, correlations among multiple process steps can be embedded into the estimated distribution. This makes it possible to construct distributions that capture multi-process tendencies that do not appear in conventional single-process distributions, thereby enabling defect judgment that accounts for multiple processes. It also allows the tolerance range for defect judgment to be flexibly adjusted by adopting means and standard deviations that differ from those of a normal distribution created solely from measurement data. On the other hand, if too many process steps are incorporated into the distribution, the reliability of the estimated distribution may deteriorate. Therefore, for accurate estimation, it is necessary to perform sufficient learning and analysis on historical data in advance to clarify data characteristics and inter-process correlations before applying the method.

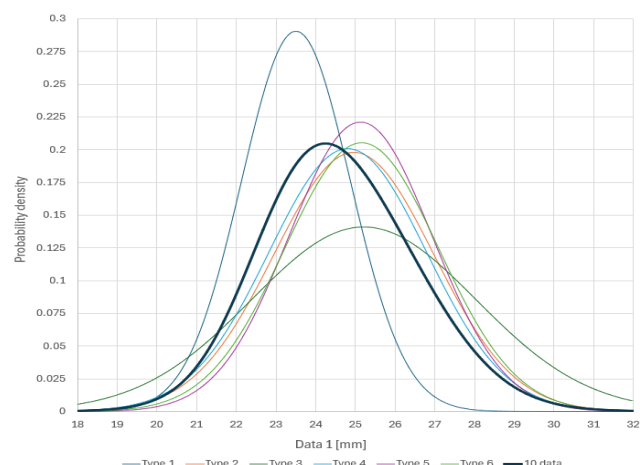


Fig.1 Each normal distribution of past data (Type 1-Type 6) and the mixture distribution based on 10 data of in-process data.