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# A new approach for quality prediction and control of multistage production and manufacturing process based on Big Data analysis and Neural Networks

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**A B S T R A C T**

As consumers care more and more about product quality, it is important to mine the deep correlations between production and manufacturing parameters and the evaluation of product quality through the analysis of industrial big data. The existing research of product quality prediction faces several major problems: the lack of diverse quality features, the poor tractability of abnormal parameters, the strong nonlinearity of parameters, the obvious sequential property of data, and the severe time lag of data. To solve these problems, this paper explores the quality prediction and control of multistage MP process (MPMP) based on big data analysis. Firstly, the prediction strategy and flow were specified for MPMP product quality prediction, and the features were extracted from MPMP product quality. After that, the MPMP product quality features were described in multiple dimensions, the attention mechanism was introduced to the prediction process. In addition, the recurrent neural network was improved, and an MPMP product quality prediction model was established on bidirectional long short-term memory (BiLSTM) network. Our model was compared with AdaBoost and XGBoost through experiments. The effectiveness of our model was demonstrated by the results of the appearance quality PQ1, and the area under the curve (AUC) for each process parameter. In general, our model is superior to other algorithms in the accuracy, mean accuracy, and precision of product quality prediction.

**A R T I C L E   I N F O**

*Keywords:*
Big data analysis;
Multistage production and manufacturing process (MPMP);
Quality prediction;
Machine learning;
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