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# Introduction to Control Charts and Machine Learning for Anomaly Detection in Manufacturing

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## Abstract

In this chapter, we provide an introduction to Anomaly Detection and potential applications in manufacturing using Control Charts and Machine Learning techniques. We elaborate on the peculiarities of process monitoring and Anomaly Detection with Control Charts and Machine Learning in the manufacturing process and especially in the smart manufacturing contexts. We present the main research directions in this area and summarize the structure and contribution of the book.

## 1 Scope of the Research Domain

Anomaly Detection is a set of major techniques with an aim to detect rare events or observations that deviate from normal behavior. Process monitoring and Anomaly Detection are becoming increasingly important to enhance reliability and productivity in manufacturing by detecting abnormalities early. For example, a vibration level in an electric motor exceeding the permissible threshold can be considered as an anomaly, it might not be considered as a fault. However, if the vibration level continues to rise and leads to motor destruction, it can be considered as faulty. Therefore, Anomaly Detection can provide advantages to manufacturing companies by reducing their downtime due to machine breakdowns by detecting a failure before this results in a catastrophic event that may cause degradation of the process and product(Lindemann et al.<sup>1</sup>). There have been various data-driven and model-based approaches to detect anomalies occurring in manufacturing systems. The most common approach to Anomaly Detection includes Control Charts and Machine Learning methods. In manufacturing, Control Charts are effective tools of Statistical Process Control(SPC) for

continuously monitoring a process as well as detecting process abnormalities to improve and optimize the process. There are many different types of Control Charts that have been developed for this purpose. In addition, Machine Learning methods have been used a lot in detecting anomalies with different applications in manufacturing such as, detecting network attacks, detecting abnormal states in machines. Finally, the interference of these two techniques is also found in literature such as the design of Control Charts, anomaly signal interpretation, and pattern recognition in Control Charts using Machine Learning techniques.

In recent years, the rapid development and wide application of advanced technologies have profoundly impacted industrial manufacturing. The recent development of information and communication technologies such as smart sensor networks and the Internet of Things (IoT) has engendered the concept of Smart Manufacturing (SM) that adds intelligence into the manufacturing process to drive continuous improvement, knowledge transfer, and data-based decision-making. In this context, the increasing volume and quality of data from production facilitate the extraction of meaningful information, predicting future states of the manufacturing system that would be impossible to obtain even by human experts. Due to recent advances in the field of SPC, there are a lot of advanced Control Charts that have been developed, thus SPC can become a powerful tool for handling many Big Data applications that are beyond the production line monitoring in the context of SM Qiu<sup>2</sup>. Also, there are many studies on Artificial Intelligence applications in SM that exploit the valuable information in data to facilitate process monitoring, defect prediction, and predictive maintenance Wang et al.<sup>3</sup>. Using multiple sensors to collect data during manufacturing enhances real-time monitoring and decision-making, but data quality should also be ensured before using it. In this case, we can use Anomaly Detection algorithms to remove outliers in the dataset. This is the first application of Anomaly Detection algorithms in smart manufacturing, in addition, it is also used a lot in different aspects of manufacturing operations such as Anomaly Detection in machine operations, detection of attacks in industrial systems, detection of mechanical anomalies before they affect product quality, ...Therefore, Anomaly Detection plays a really important part in smart manufacturing. Lopez et al.<sup>4</sup> categorized anomalies in machines, controllers, and networks along with their detection mechanisms, and unify them under a common framework to allows the identification of gaps in Anomaly Detection in SM systems that should be addressed in future studies solutions.

In summary, the existing knowledge on Anomaly Detection with the applications in manufacturing is classified as Machine Learning and statistical approach. The statistical Anomaly Detection approach like Control Charts can be developed with little computational effort. However, their

effectiveness has been proven during a long period of industrial application. Therefore, an effort should be made to develop advanced Control Charts for application in modern industrial contexts, see Tsung et al.<sup>5</sup>, Qiu<sup>2</sup>, and Zwetsloot et al.<sup>6</sup> for some examples. However, in SM contexts where assumptions about data distribution and independence are violated, Anomaly Detection methods will come into play, although they require considerable computational effort and resources. For example, Nguyen et al.<sup>7</sup> have developed a novel deep hybrid model for Anomaly Detection for multivariate time series without using any assumptions for the distribution of prediction errors. The autoencoder LSTM (Long Short-Term Memory networks) is used as a feature extractor to extract important representations of the multivariate time series input and then these features are input to OCSVM (One Class Support Vector Machine) for detecting anomalies. This model results in better performance compared to the performance from several previous studies. Therefore, efforts are needed to develop Machine Learning Anomaly Detection methods that are suitable for applications in SM. Finally, there are studies that combine both techniques to develop hybrid methods to combine the strengths of both techniques Lee et al.<sup>8</sup>, Qiu and Xie<sup>9</sup>.

## 2 Main Features of This Book

The key features of this book are given as follows:

1. Machine Learning has many applications in the development, pattern recognition, and interpreting of Control Charts. Especially applying Machine Learning to design Control Charts to monitor and detect anomalies in non-Gaussian, auto-correlated processes, or Non-stationary processes are important topics.
2. Advanced Control Charts are designed for monitoring Time-Between-Events-and-Amplitude Data, First-order Binomial Autoregressive Process. All of these studies aim to address the monitoring of manufacturing processes where the assumption of independence is violated.
3. To monitor the processes correlated data, Machine Learning-based Control Charts for monitoring categorical event series and monitoring serially correlated data are introduced in this book. In contrast to other methods, these new methods are more efficient in monitoring the correlated process data.
4. To detect anomalies in processes with Machine Learning, Tree-based approaches, autoencoder approaches, L1 SVDD (Support Vector Data Description), and L2 SVDD approaches are given in detail.

5. As an industrial application of Anomaly Detection, a comprehensive review and new advances of feature engineering techniques and health indicator construction methods for fault detection and diagnostic of engineering systems are introduced.
6. The case studies presented and analyzed in each chapter will help researchers, students, and practitioners understand and know how to apply these advanced methods in practice. The design parameters, as well as some source code of the tests and algorithms, are also shared with readers.

### 3 Structure of the Book

This book uncovers fundamental principles and recent developments in the advanced Control Charts and new Machine Learning approaches for Anomaly Detection in the manufacturing process and especially in the smart manufacturing contexts. The purpose of this book is to comprehensively present recent developments of Anomaly Detection techniques in manufacturing and to systemize these developments in new taxonomies and methodological principles with the application in SM to shape this new research domain. By approaching Anomaly Detection by both statistics and Machine Learning, this book also promotes cooperation between the research communities on SPC and Machine Learning to jointly develop new Anomaly Detection approaches that are more suitable for the 4.0 industrial revolution. This book addresses the needs of both researchers and practitioners to uncover the challenges and opportunities of Anomaly Detection techniques with the applications to manufacturing. The book will also provide ready-to-use algorithms and parameter sheets so readers and practitioners can design advanced Control Charts and Machine Learning-based approaches for Anomaly Detection in manufacturing. Case studies will also be introduced in each chapter to help readers and practitioners easily apply these tools to real-world manufacturing processes. The book contains 10 chapters.

In the Introductory chapter "Introduction to Control Charts and Machine Learning for Anomaly Detection in Manufacturing," the book editor Kim Phuc Tran elaborates on the peculiarities of Anomaly Detection problems using Control Charts and Machine Learning. He determines recent research streams and summarizes the structure and contribution of the book.

Phuong Hanh Tran, Adel Ahmadi Nadi, Thi Hien Nguyen, Kim Duc Tran, and Kim Phuc Tran investigate in their chapter, "Application of Machine Learning in Statistical Process Control Charts: a survey and perspective", a survey and perspective about the development of Machine Learning-based Control Charts, Control Chart Pattern Recognition method using

Machine Learning, and interpreting of out-of-control signals. This chapter fills the gap in the literature by identifying and analyzing research on the application of Machine Learning in statistical process Control Charts. The authors review and discuss open research issues that are important for this research stream.

Philippe Castagliola, Giovanni Celano, Dorra Rahali, and Shu Wu develop in their chapter, “Control Charts for Monitoring Time-Between-Events-and-Amplitude Data,” a study to investigate several Time-Between-Events-and-Amplitude Data Control Charts and to open new research directions.

Maria Anastasopoulou and Athanasios C. Rakitzis develop in their chapter, “Monitoring a First-order Binomial Autoregressive Process with EWMA and DEWMA Control Charts,” one-sided and two-sided EWMA (Exponentially Weighted Moving Average) and Double EWMA Control Charts for monitoring an integer-valued autocorrelated process with bounded support.

Christian H. Weiß develops in his chapter, “On Approaches for Monitoring Categorical Event Series” a survey of approaches for monitoring categorical event series. Also, rule-based procedures from Machine Learning are used for the monitoring of categorical event series, where the generated rules are used to predict the occurrence of critical events.

Xiulin Xie and Peihua Qiu develop in their chapter, “Machine Learning Control Charts for Monitoring Serially Correlated Data,” an approach of using certain existing Machine Learning Control Charts together with a recursive data de-correlation procedure.

Tommaso Barbariol, Filippo Dalla Chiara, Davide Marcato and Gian Antonio Susto develop in their chapter, “A review of Tree-based approaches for Anomaly Detection,” a review of several relevant aspects of the methods, like computational costs and interpretability traits.

Anne-Sophie Collin and Christophe De Vleeschouwer develop in their chapter, “Joint use of skip connections and synthetic corruption for Anomaly Detection with autoencoders” a detection of abnormal structure in images based on the reconstruction of a clean version of this query image.

Edgard M. Maboudou-Tchao and Charles W. Harrison develop in their chapter, “A comparative study of L1 and L2 norms in Support Vector Data Descriptions” a comparative study of L1 and L2 norms in Support Vector Data Descriptions. They apply the L1 SVDD and L2 SVDD to a real-world dataset that involves monitoring machine failures in a manufacturing process.

Khanh T. P. Nguyen develops in her chapter, “Feature engineering and health indicator construction for fault detection and diagnostic” a comprehensive review and new advances of feature engineering techniques and health indicator construction methods for fault detection and diagnostic of engineering systems.

## 4 Conclusion

This book, consisting of 10 chapters, aims to address both research and practical aspects in Control Charts and Machine Learning with an emphasis on the applications. Each chapter is written by active researchers and experienced practitioners in the field aiming to connect the gap between theory and practice and to trigger new research challenges in Anomaly Detection with the applications in manufacturing. The strong digital transformation that has been taking place in manufacturing creates a lot of data with different structures from the process, Anomaly Detection with its applications becomes more important. This book is an important reference focused on advanced Machine Learning algorithms and Control Charts to help managers extract anomalies from process data, which can aid decision-making, early warning of failures, and help improve the quality and productivity in manufacturing.

## References

- [1] B. Lindemann, F. Fesenmayr, N. Jazdi, and M. Weyrich. Anomaly detection in discrete manufacturing using self-learning approaches. *Procedia CIRP*, 79:313–318, 2019.
- [2] P. Qiu. Big data? Statistical process control can help! *The American Statistician*, 74(4):329–344, 2020.
- [3] J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu. Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems*, 48:144–156, 2018.
- [4] F. Lopez, M. Saez, Y. Shao, E.C. Balta, J. Moyne, Z.M. Mao, K. Barton, and D. Tilbury. Categorization of anomalies in smart manufacturing systems to support the selection of detection mechanisms. *IEEE Robotics and Automation Letters*, 2(4):1885–1892, 2017.
- [5] F. Tsung, K. Zhang, L. Cheng, and Z. Song. Statistical transfer learning: A review and some extensions to statistical process control. *Quality Engineering*, 30(1):115–128, 2018.

- [6] I.M. Zwetsloot, T. Mahmood, and W.H. Woodall. Multivariate time-between-events monitoring: An overview and some overlooked underlying complexities. *Quality Engineering*, pages 1–13, 2020.
- [7] H.D. Nguyen, K.P. Tran, S. Thomassey, and M. Hamad. Forecasting and Anomaly Detection approaches using LSTM and LSTM Autoencoder techniques with the applications in supply chain management. *International Journal of Information Management*, 57:102282, 2021.
- [8] S. Lee, M. Kwak, K.L. Tsui, and S.B. Kim. Process monitoring using variational autoencoder for high-dimensional nonlinear processes. *Engineering Applications of Artificial Intelligence*, 83:13–27, 2019.
- [9] P. Qiu and X. Xie. Transparent Sequential Learning for Statistical Process Control of Serially Correlated Data. *Technometrics*, (just-accepted): 1–29, 2021.