# CONTROL CHART PATTERNS RECOGNITION USING RUN RULES AND FUZZY CLASSIFIERS CONSIDERING LIMITED DATA

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To my beloved family

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## ABSTRACT

Statistical process control chart is a common tool used for monitoring and detecting process variations. The process data streams, when graphically plotted on control chart reveal useful patterns. These patterns can be associated with possible assignable causes if properly recognized. These patterns detections are useful for process diagnostic. Different types of control chart pattern recognition methods are reported in literature. Most of the existing data-driven methods require a large amount for training data before putting into practice. Short production run and short product life cycle processes are usually constrained with limited data availability. Thus there is a need to investigate and develop an effective control chart pattern recogniser (CCPR) methods for process monitoring with limited data. Two methods were investigated in this study to recognize fully developed control chart patterns for process with limited data on *X*-bar chart. The first method was combination of selected run rules, as run rules do not require training data. Classifiers based on fuzzy set theory were the second method. The performance of these methods was evaluated based on percent correct recognition. The methods proposed in this study significantly reduced the requirements of training data. Different combination of Nelson's run rules; $R_2$,$R_5$,$R_6$ for shift and trend, $R_3$,$R_5$,$R_6$ for cyclic, $R_4$,$R_5$,$R_8$ for systematic and $R_7$ for stratification patterns were found effective for recognizing. Differentiating between the shift and trend patterns remains challenging task for the run rules. Heuristic based Mamdani fuzzy classifier with fuzzy set simplification operations using statistical features gave more than ninety percent correct patterns recognition results. Adaptive neuro fuzzy inference system (ANFIS) fuzzy classifier with fuzzy c-mean using statistical features gave more prominent results. The findings suggest that the proposed methods can be used in short production run and the process with limited data. The fuzzy classifiers can be further studied for different input representation.

# ABSTRAK

Carta kawalan adalah teknik yang lazim digunakan untuk mengesan perubahan variasi di dalam proses. Data proses yang dicartakan secara grafikal dapat menyerlahkan corak variasi yang berguna. Corak-corak berkenaan boleh dikaitkan dengan penyebab masalah proses jika di kesan secara terperinci, dimana maklumat ini berguna untuk proses diagnostik. Terdapat pelbagai kaedah pengecaman pola carta kawalan yang telah dilaporkan di dalam literatur. Kebanyakan kaedah sediada memerlukan sejumlah data latihan yang besar sebelum pengecaman dapat dilaksanakan. Pengeluaran produk yang memiliki jangka hayat yang pendek selalunya menghadapi kekangan data yang tidak mencukupi untuk pengawasan proses. Oleh yang demikian,adalah perlu untuk menyiasat dan membangunkan teknik yang berkesan untuk pengecaman pola carta kawalan (CCPR) bagi pemerhatian proses yang  mempunyai data yang terhad. Dua kaedah telah dikaji untuk pengecaman pola pada carta kawalan x-bar yang telah berkembang sepenuhnya. Kaedah pertama menggunakan gabungan aturan larian (run rules) terpilih yang tidak memerlukan data latihan. Manakala,kaedah kedua adalah pengelasan pola berdasarkan teori set *Fuzzy*. Prestasi kaedah-kaedah yang dikaji dinilai berdasarkan peratusan ketepatan pengecaman. Kaedah pengecaman yang dicadangkan di dalam kajian ini berjaya mengelakkan dan mengurangkan keperluan data latihan. Dapatan kajian dapat dirumusakan kombinasi. Aturan Nelson $R_2,R_5,R_6$ untuk corak anjakan dan trend, Aturan $R_3,R_5,R_6$ untuk corak kitaran,Aturan $R_4,R_5,R_8$ untuk corak sistematik and Aturan $R_7$ untuk corak stratifikasi. Walubagaimanapun, kaedah aturan larian masih tidak mampu untuk membezakan sepenuhnya di antara pola anjakan dan trend. Kaedah heuristik *Fuzzy Mamdani* dengan data input ciri statistikal telah berjaya mengecam dengan ketepatan lebih daripada 90 peratus. Sistem inferens adaptif *Neuro Fuzzy* (ANFIS) dengan *Fuzzy c-mean* pula berjaya memberi keputusan yang lebih baik. Hasil kajian menunjukkan kaedah yang dicadangkan berkesan untuk digunakan dalam pengawasan dan diagnosis proses pengeluaran jangka singkat dengan data proses yang terhad. Kaedah pengelasan *Fuzzy* ini memerlukan kajian lanjutan untuk menilai keberkesanan kaeadah perwakilan input yang berlaianan.

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# CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

The Shewhart control chart, developed in 1924, has been widely used in the quality control and monitoring of manufacturing processes. It is still one of the most valuable and important tool in statistical process control today. The control charts are useful in finding whether a process exhibit natural causes of variation or unnatural causes of variation. A process is marked out of control, when a point falls outside the required control limits. Previous points plotted on control chart, some time follow specific patterns. Some of patterns are called normal patterns and some are called abnormal patterns. Abnormal patterns are due to unnatural variations and provide important information regarding opportunities for process and product quality improvement. The occurrence of abnormal patterns specifies that a process is unstable, and corrective actions should be taken. to find out the root cause of variations (El-Midany *et al.*, 2010). Also it is clear that particular abnormal pattern on a control chart is often related to some specific set of assignable causes and these patterns give clues about root cause of the unnatural variations (Western Electric Company, 1958). Therefore, identification and analysis of abnormal patterns on control charts is an important characteristic of statistical process control, in order to diagnose the causes of out of control and unstable systems. Early detection of these abnormal patterns and corresponding diagnosis prevent catastrophic failures.

Shewhart control chart by itself does not gives information about patterns and corresponding causes because it ignores the previous points and only concern with present data points. To overcome this issue different methods have been investigated by researchers, collectively called control chart pattern recognition (CCPR). The purpose of these methods are to analyse previous data points, in order to find information about what type of special causes are present for unnatural variations. The early methods to find out patterns on control chart reported in literatures are supplementary run rules methods. Some of well-known run rules reported in literature are Western Electric rules (Western Electric Company, 1958), Nelson rules (Nelson, 1984).

Traditionally, SPC chart patterns have been analysed and interpreted manually by supplementary run rules. Due to popularity of expert systems in 1980s several researchers like Swift (1987) and Cheng (1989) proposed merge of statistical process control methods with expert system. Automatic pattern recognition is considered more superior as compared to manual methods. One of the early useful expert system tools is artificial neural networks (ANN) and several researchers use this tool for SPC chart pattern recognition. The inherent useful properties and capabilities of neural networks such as non-linearity, input-output mapping, adaptability and fault tolerance inspired the use of ANN many researcher (Haykin and Network, 2004) . Since then, many researchers have proposed various ANN-based SPC chart pattern recognition schemes.

The other soft computing techniques like fuzzy set theory as classifiers are proposed by limited researchers. Most of the previous fuzzy methods such as Zarandi *et al.* ,2008 is based on the run rules for detecting process stability only considering probability of different run rules. Limited work has been reported for control chart pattern recognition using fuzzy classifiers. Feature base fuzzy classifiers are limited in literature. The author found only one paper by Wang and Kuo (2007) that has proposed wavelet features for classification of abnormal patterns. The author is unable to locate previous work on the hybrid methods like neuro-fuzzy and adaptive neuro-fuzzy for control chart pattern recognition using statistical features only.

The Support vector machine method nowadays, gains popularity due to its generalization properties and good recognition accuracy is recently reported in literature. The hybrid support vector machine (SVM) along with fuzzy clustering technique is also reported in the literature. The methods especially ANN and hybrid Adaptive neuro-fuzzy system require training data prior to application into practical problems.

Two types of input data representation have been proposed in literatures. One is the raw data input representation which after normalizing and standardizing used directly for training and testing of ANN and other hybrid types of schemes. Second input representation of data is features based, in which suitable features are extracted from data, and these features are used for testing and training of the schemes. Different types of features have been proposed by various researchers. Shape features, statistical features and wavelet denoise features are famous in literatures. Some basic issues exist in control chart patterns recognition(CCPR) field described by Hachicha and Ghorbel (2012) and Masood and Hassan (2010). The process with limited data like short production runs needs suitable design of CCPR in terms of selection of methods and design of recognizers or classifiers.

## 1.2 Problem Statement

Control chart pattern recognition is important for process monitoring, because abnormal patterns recognition on control charts can lead to root of specific assignable causes. Majority of existing methods for CCPR such as ANN,SVM etc. require extensive training data before the recognizers implementation. Due to short product life cycle and corresponding short runs of products limited training data are usually available. The methods which required extensive data prior to application into real system have several issues due to limited data availability. The limitation of existing methods and problems in short production run are summarized below:

(a) Run rules can be used for short run and limited data as no training data is required. Contrasting views about run rules in literature is present about pattern recognition. Some researchers argued that run rules are not suitable for control chart pattern recognitions while some researchers recommended run rules for pattern identification. The run rules were used individually by many researchers in literatures in order to increase sensitivity of control chart. Multiple run rules when applied simultaneously, may increases the false alarm. It is also reported in literature that runs rules do not identify pattern explicitly. Which run rules overlap for patterns and which are identified by run rules correctly also not investigated in literature.

(b) The supervised ANN-based recognizer is suitable for mass production process due to sufficient data availability. Short production run and short product life cycle and corresponding limited data availability of processes lessen the effectiveness of ANN recognizer. There is need to investigate recognizing methods for control chart patterns (CCPs) with limited data. The soft computing methods based on fuzzy set theory still not widely investigated for short run processes.

## 1.3 Research Objectives

The main objectives of the project are stated below:

(a) To investigate and find suitable run rules combinations for control chart patterns recognition focusing on limited process data.
(b) To design and develop control chart patterns recognizers for limited process data using fuzzy set theory.

## 1.4 Research Questions

The objectives discussed above can be strengthening if we formulate some basic questions. These questions when answered can significantly fulfil the research objective requirements. Some of the basic questions formulated are given below:

Q1: Are run rules suitable for CCPR with limited data?
Q2: Which combination of run rules is suitable to recognize various patterns?
Q3: What are the limitations of run rules for CCPR?
Q4: Which soft computing classifiers are suitable for limited data?

Q5: Which types of features are suitable for classifiers considering limited data?

Q6: What is the suitable set of features for classifiers considering limited data?

## 1.5 Scope of the Project

This project is limited to the univariate pattern recognition generated in MATLAB environment using random generation techniques. The process mean is considered as main parameters of control and different patterns are generated only on X-bar Shewhart control charts for this study. Only discrete component production is considered in this study. The main scope of the project is to simulate the control chart patterns in MATLAB using random generation techniques. The comparison of different run rules and feature base fuzzy CCPR methods will be compared to recognizer proposed in literature. The design includes selecting suitable combination of features and investigating membership function , IF-THEN rules for fuzzy base classifiers. The MATLAB software has been used for coding and programming purposes. The fully developed control chart patterns will be considered in this study only within window size of 20.

Also we assumed that process is running normal. The sample size of five is considered. The averages of five and above is more sensitive to detect shift according to central limit theorem. Central limit theorem state that the distribution of sample averages is approximately behaving normal even if the population from which the sample is drawn is not normally distributed. The approximation improves as the sample size increaseses.( Benbow and Broome, 2009).

## 1.6 Importance of Study

This research work intends to contribute to design and development of CCPR classifiers for limited data. This study is important since short product life cycle is becoming more common nowadays.

## 1.7 Summary

This chapter briefly explains the problem statement and objective of the project. First the background of the problem was discussed. Then problem statement, objectives and research questions were formulated. Also the scope of the projects was outlined. The next chapter described the literature review in detail.

# REFERENCES


A Viattchenin, D., Tati, R., & Damaratski, A. (2013). Designing Gaussian membership functions for fuzzy classifier generated by heuristic possibilistic clustering. *Journal of Information and Organizational Sciences*, *37*(2), 127-139.

Ajiboye, A.B. and Weir, R. F. (2005). A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *13*(3), 280–291.

Al-Assaf, Y. (2004). Recognition of control chart patterns using multi-resolution wavelets analysis and neural networks. *Computers & Industrial Engineering*, *47*(1), 17–29.

Alcock, 1999. http://archive.ics.uci.edu/ml/databases/synthetic control/ synthetic control. data.html

Al-Jarrah, O. and Halawani, A. (2001). Recognition of gestures in Arabic sign language using neuro-fuzzy systems. *Artificial Intelligence*, *133*(1), 117–138.

Avakh Darestani, S., & Aminpour, N. (2014). Short-Run Control Chart for Multiproduct with Multi-Items Based on Unequal Means and Variances. *Journal of Quality and Reliability Engineering*, *2014*.

Benbow,W.D,Broome W.W, (2009). The certified reliability engineer handbook. ASQ Quality Press.

Bennasar, M., Hicks, Y., & Setchi, R. (2015). Feature selection using joint mutual information maximisation. *Expert Systems with Applications*, *42*(22), 8520-8532

Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm.*Computers & Geosciences*, *10*(2-3), 191-203.

Britt, K.A., Ramírez, B. and Mistretta, T. (2016). Process monitoring using statistical stability metrics: Applications to biopharmaceutical processes. *Quality Engineering*, *28*(2), 193–211.

Champ, C. W., & Woodall, W. H. (1987). Exact results for Shewhart control charts with supplementary runs rules. *Technometrics*, *29*(4), 393–399.

Cheng, C. S. (1989). *Group technology and expert systems concepts applied to statistical process control in small-batch manufacturing.* PhD disertation, Arizona State University.

Cheng, C.S. (1997). A neural network approach for the analysis of control chart patterns. *International Journal of Production Research*, *35*(3), 667–697.

Cheng, C.S., Huang, K.K. and Chen, P. W. (2015). Recognition of control chart patterns using a neural network-based pattern recognizer with features extracted from correlation analysis. *Pattern Analysis and Applications*, *18*(1), 75–86.

Deer, P. J., & Eklund, P. (2003). A study of parameter values for a Mahalanobis distance fuzzy classifier. *Fuzzy Sets and Systems*, *137*(2), 191-213.

De la Torre Gutierrez, H. and Pham, D. T. (2016). Estimation and generation of training patterns for control chart pattern recognition. *Computers & Industrial Engineering*, *95*, 72–82.

Demuth, H., Beale, M. and Hagan, M. (2005). Neural network toolbox users guide. *The Mathworks, Natick, MA.*

Dominique A. Heger. (2010). *An Introduction to Artificial Neural Networks (ANN) - Methods, Abstraction, and Usage;* DHT Technologies.

Ebrahimzadeh, A., & Ranaee, V. (2011). High efficient method for control chart patterns recognition. *Acta technica ČSAV*, *56*(1), 89-101.

El-Midany, T.T., El-Baz, M.A. and Abd-Elwahed, M. S. (2010). A proposed framework for control chart pattern recognition in multivariate process using artificial neural networks. *Expert Systems with Applications*, *37*(2), 1035–1042. http://doi.org/10.1016/j.eswa.2009.05.092

Gacek, A., & Pedrycz, W. (Eds.). (2011). *ECG signal processing, classification and interpretation: a comprehensive framework of computational intelligence*. Springer Science & Business Media

Gauri, S. K., & Chakraborty, S. (2007). A study on the various features for effective control chart pattern recognition. The International Journal of Advanced Manufacturing Technology, 34(3), 385-398.

Gauri, S. K., & Chakraborty, S. (2008). Improved recognition of control chart patterns using artificial neural networks. *International Journal of Advanced Manufacturing Technology*, *36*(11-12), 1191–1201.

Gauri, S. K., & Chakraborty, S. (2009). Recognition of control chart patterns using improved selection of features. Computers & Industrial Engineering, 56(4), 1577-1588

Griffiths, D., Bunder, M., Gulati, C. and Onizawa, T. (2010). The Probability of an Out of Control Signal from Nelson's Supplementary Zig-Zag Test. *Journal of Statistical Theory and Practice*, *4*(4), 609–615.

Grzegorzewski, P. and Hryniewicz, O. (2000). Soft methods in statistical quality control. *Control and Cybernetics*, *29*(1), 119–140.

Guh, R.S. (2005). A hybrid learning-based model for on-line detection and analysis of control chart patterns. *Computers & Industrial Engineering*, *49*(1), 35–62.

Guh, R.S., and Tannock, J.D.T. (1999). Recognition of Control Chart Concurrent Patterns Using a Neural Network Approach. *International Journal of Production Research*, *37*, 1743–1765.

Gülbay, M. and Kahraman, C. (2006). Development of fuzzy process control charts and fuzzy unnatural pattern analyses. *Computational Statistics & Data Analysis*, *51*(1), 434–451.

Güler, I. and Übeyli, E. D. (2005). Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients. *Journal of Neuroscience Methods*, *148*(2), 113–121.

Gulley, N. (1996). Fuzzy logic toolbox for use with MATLAB.

Gwee, B.H., Lim, M.H. and Soong, B. H. (1996). Self-adjusting diagnostic system for the manufacture of crystal resonators. *IEEE Transactions on Industry Applications*, *32*(1), 73–79.

Hachicha, W. and Ghorbel, A. (2012). A survey of control-chart pattern-recognition literature (1991–2010) based on a new conceptual classification scheme. *Computers & Industrial Engineering*, *63*(1), 204–222.

Haghtalab, S., Xanthopoulos, P., & Madani, K. (2015). A robust unsupervised consensus control chart pattern recognition framework. *Expert Systems with Applications*, *42*(19), 6767-6776.

Hassan, A. (2011). An improved scheme for online recognition of control chart patterns. *International Journal of Computer Aided Engineering and Technology*, *3*(3-4), 309–321.

Hassan, A., Baksh, M. S. N., Shaharoun, A. M., & Jamaluddin, H. (2011, July). Feature selection for SPC chart pattern recognition using fractional factorial experimental design. In *Intelligent Production Machines and System: 2nd I* IPROMS Virtual International Conference, In: D. T. Pham, EE Eldukhri, and AJ Soroka Ed., Elsevier* (pp. 442-447).

Hassan, A., Baksh, M.S.N., Shaharoun, A.M. and Jamaluddin, H. (2003). Improved SPC chart pattern recognition using statistical features. *International Journal of Production Research, 41*(7), 1587–1603.

Haykin, S. and Network, N. (2004). *A comprehensive foundation. Neural Networks,2(2004)*.

Heizer, Rander,  and B. R. ". (2013). *Operation Management, Sustainability and Supply Chain management*.

Isermann, R., & Ballé, P. (1997). Trends in the application of model-based fault detection and diagnosis of technical processes. *Control Engineering Practice*, *5*(5), 709–719. http://doi.org/10.1016/S0967-0661(97)00053-1

ISO. (1991). Shewhart Control Charts. *International Organization for Standardization, Switzerland,*.

Jang, J. S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, *23*(3), 665-685.

Joaquim, P. M. D. S., & Marques, S. (2007). Applied statistics using SPSS, statistica, Matlab and R. *Springer Company USA*, 205-211.

Kahraman, C., Tolga, E. and Ulukan, Z. (1995). Using triangular fuzzy numbers in the tests of control charts for unnatural patterns. In Emerging Technologies and Factory Automation. *TFA'95, Proceedings., 1995 INRIA/IEEE Symposium on*, *3*, 291–298.

Kazemi, M.S., Kazemi, K., Yaghoobi, M.A. and Bazargan, H. (2016). A hybrid method for estimating the process change point using support vector machine and fuzzy statistical clustering. *Applied Soft Computing*, *40*, 507–516.

Khajehzadeh, A., & Asady, M. (2015) Recognition of Control Chart Patterns Using adaptive neuro-fuzzy inference system and Efficient Features. International Journal of Scientific & Engineering Research 6(9).

Khoo, M.B. and Ariffin, K.N.B. (2006). Two improved runs rules for the Shewhart X control chart. *QUALITY ENGINEERING*, *18*(2), 173–178.

Khormali, A., & Addeh, J. (2016). A novel approach for recognition of control chart patterns: Type-2 fuzzy clustering optimized support vector machine. *ISA transactions*, *63*, 256-264

Klein, M. (2000). Two alternatives to the Shewhart X control chart. *Journal of Quality Technology*, *32*(4), 427.

Lavangnananda, K. and Waiwing, S. (2015). Effectiveness of Different Preprocessing Techniques on Classification of Various Lengths of Control Charts Patterns. *Procedia Computer Science*, *69*, 44–54.

Lim, S. A. H., Antony, J., & Albliwi, S. (2014). Statistical Process Control (SPC) in the food industry – A systematic review and future research agenda. *Trends in Food Science & Technology*, *37*(2), 137–151. http://doi.org/10.1016/j.tifs.2014.03.010

Lucy-Bouler, T. L. (1991). Using autocorrelations, CUSUMs and runs rules for control chart pattern recognition: An expert system approach.

Lucy-Bouler, T. L. (1993). Problems in control chart pattern recognition systems. *International Journal of Quality & Reliability Management*, *10*(8).

Mahesh Mathur, ARNONM, H. (1992). A very simple set of process control rules. *Quality Engineering*, *5*(1), 21–29.

Marques, P. A., Cardeira, C. B., Paranhos, P., Ribeiro, S., & Gouveia, H. (2015). Selection of the most suitable statistical process control approach for short production runs: a decision-model.*International Journal of Information and Education Technology*, *5*(4), 303.

Masood, I. and Hassan, A. (2010). Issues in development of artificial neural network-based control chart pattern recognition schemes. *European Journal of Scientific Research*, *39*(3), 366–355.

Montgomery, D. C. (2009). Statistical Quality Control-A Modern Introduction. John Whiley & Sons. Inc., New York

Nauck, D. and Kruse, R. (1997). A neuro-fuzzy method to learn fuzzy classification rules from data. *Fuzzy Sets and Systems*, *89*(3), 277–288.

Nelson, L. S. (1985). Interpreting Shewharts x-bar chart. *Journal of Quality Technology*, *17*, 114–116.

Nelson, L. S. (1989). Standardization of Shewhart control charts. *Journal of Quality Technology*, *21*(4), 287–289.

Nelson, L.S. (1984). The Shewhart control chart–tests for special causes. *Journal of Quality Technology*, *16*(4), 237–239.

Noskievičová, D. (2013). Complex Control Chart Interpretation. *International Journal of Engineering Business Management*, *5*. http://doi.org/10.5772/DOI

Pham, D.T. and Wani, M. A. (1997). Feature-based control chart pattern recognition. *International Journal of Production Research*, *35*(7), 1875–1890.

Riaz, M., Mehmood, R. and Does, R. J. (2011). On the performance of different control charting rules. *Quality and Reliability Engineering International*, *27*(8), 1059–1067.

Sancho, J., Martínez, J., Pastor, J.J., Taboada, J., Piñeiro, J.I. and García-Nieto, P. J. (2014). New methodology to determine air quality in urban areas based on runs rules for functional data. *Atmospheric Environment*, *83*, 185–192.

Severson, K., Chaiwatanodom, P., & Braatz, R. D. (2015). Perspectives on Process Monitoring of Industrial Systems. *IFAC-PapersOnLine*, *48*(21), 931–939. http://doi.org/10.1016/j.ifacol.2015.09.646

Sugeno, M., & Kang, G. T. (1988). Structure identification of fuzzy model. Fuzzy sets and systems, 28(1), 15-33.

Sumathi, S., Surekha, P., & Surekha, P. (2010). Computational intelligence paradigms: theory and applications using MATLAB (Vol. 1). Boca Raton, FL, USA:: CRC Press.

Swift, J. A. (1987). *Development of a knowledge-based expert system for control-chart pattern recognition and analysis*. *Oklahoma State Univ., Stillwater, OK (USA).* PhD disertation, Oklahoma State University.

*Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. IEEE transactions on systems, man, and cybernetics, (1), 116-132.*

Taur, J.S. and Tao, C. W. (2000). A new neuro-fuzzy classifier with application to on-line face detection and recognition. *Journal of VLSI Signal Processing Systems for Signal, Image and Video Technology*, *26*(3), 397–409.

Taylor, Bernard W., et al. (2013). *Introduction to management science. Upper Saddle River, NJ: Prentice Hall, 2004.* (P. E. Limited, Ed.) (Eleventh).

Vapnik, V. (2013). *The nature of statistical learning theory*. Springer science & business media

Wang, C. H., & Kuo, W. (2007). Identification of control chart patterns using wavelet filtering and robust fuzzy clustering. *Journal of Intelligent Manufacturing*, *18*(8), 343–350.

Wang, J., Kochhar, A.K. and Hannam, R.G. (1998). Pattern recognition for statistical process control charts. *The International Journal of Advanced Manufacturing Technology*, *14*(2), 99–109.

Western Electric Company. (1958). *Statistical quality control handbook. The Company.*

Wilamowski, B. M. (2009). Neural network architectures and learning algorithms. *IEEE Industrial Electronics Magazine*, *3*(4), 56–63.

Xanthopoulos, P., & Razzaghi, T. (2014). A weighted support vector machine method for control chart pattern recognition. *Computers & Industrial Engineering*, *70*, 134-149.

Yin, S., Ding, S.X., Xie, X. and Luo, H. (2014). A Review on Basic Data-Driven Approaches for Industrial Process Monitoring. *IEEE Transactions on Industrial Electronics*, *61*(11), 6418–6428. http://doi.org/10.1109/TIE.2014.2301773

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338–353.

Zaman, B., Riaz, M. and Abbasi, S. A. (2016). On the Efficiency of Runs Rules Schemes for Process Monitoring. *Quality and Reliability Engineering International*, *32*(2), 663–671.

Zarandi, M.F., Alaeddini, A. and Turksen, I. B. (2008). A hybrid fuzzy adaptive sampling–run rules for Shewhart control charts. *Information Sciences*, *178*(4), 1152–1170.