Original Article

Regression Control Charts-A Survey

Nancy, M[1], Hemlata Joshi[2], B.V. Dhandra[3]

[1,2,3] Department of Statistics and Data Science, CHRIST (Deemed to be University), Bengaluru, India
Email: [1] nancy9b@gmail.com, [2] hemlata.joshi28@gmail.com, [3]b asanna.veeranna@christuniversity.in
*Corresponding Author: Nancy, M
Department of Statistics and Data Science, CHRIST (Deemed to be University), Bengaluru, India
Email: nancy9b@gmail.com
DOI: 10.47750/pnr.2023.14.03.142

Abstract

Statistical quality control is a method and graphical procedure that plays a vital role in monitoring and controlling the process for the targeted quality. Control charts can be viewed in two different ways: standard Shewhart control charts with their variations, and control charts that are influenced by interrelated independent variables for the process shift. The combination of conventional control charts and regression analysis is called regression control charts. Regression control charts assist in lowering overall process variability, inspection, and rejection costs, also monitoring and projecting performance ranges. This paper considers 43 articles on various regression control charts during 2010-2021 for the survey. The widespread construction of regression control charts in general and the research carried out in the construction of regression control charts in the presence of multicollinearity, in particular, is discussed. The charts are categorized based on linear, non-linear, and generalized regression models. This survey aims to aid researchers in their understanding of various features of regression control charts. This is crucial because numerous researchers approach issues in a variety of ways, making it clear that there are various points of view.

Keywords: Control Chart, Literature Review, Multicollinearity, Regression Control Chart, Statistical Process Control

I. INTRODUCTION

Walter Andrew Shewhart [1931] is the first person who introduced the control charts; since then, a lot of research is carried out on control charts and the improved control charts are used for different process data to check the shift. Control charts are basically used to identify whether a process is stable and under control or unstable and out of control. It assists quality teams in monitoring the performance of a process and identifies the specific or assignable causes for issues that obstruct peak performance. The basic form of a Shewhart control chart compares process observations with a pair of control limits. In constructing a Shewhart chart, two basic assumptions are made:

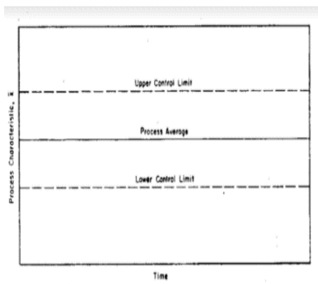
i. Process data is independently distributed and
ii. The distribution function underlying process data is normal.

The violation of these assumptions may lead to an erroneous construction of control limits. Alwan and Roberts (1988) report that about 85% of a sample of 235 control chart applications have incorrect control limits. Most of these erroneous charts are due to the violation of independently distributed data assumption made in the Shewhart chart when the influence of autocorrelation is present in the data. For auto-correlated data following three general approaches are recommended in the literature.

- Fit an ARIMA model to the data and then design conventional control charts such as Shewhart and CUSUM.
- Modify the control charts to accommodate the autocorrelation factor and monitor the auto-correlated observations.
- Eliminate the autocorrelation by applying an engineering controller [Montgomery, 1991; Testik 2005].

It is proved that Shewhart control charts are unreliable when systemic trends exist in-process data (Alwan and Roberts, 1988). Shewhart charts are strong enough in identifying big changes in the process mean or variance however, smaller changes such as 1σ or 2σ change in the mean are difficult to detect. In Shewhart control charts quality characteristic measurement is for single observations whereas for regression control charts quality characteristic measurement happens within one subgroup. Therefore, regression control charts are found to be useful in monitoring and analyzing processes with trends. Hence, the practitioners typically implement regression-based control charts to monitor a process with the systemic trends instead of standard Shewhart control charts (Utley and May, 2008). Therefore, a lot of research is carried out on regression control charts.

Regression Control Charts (RCC) are effective statistical process control techniques that combine regression analysis and conventional control charts for maintaining the quality of the product. These regression control charts are designed and developed to govern the dynamic nature of control charts instead of static control charts i.e. control limit lines are parallel to the regression line instead of the horizontal line as shown in Figures 1.1 and 1.2.



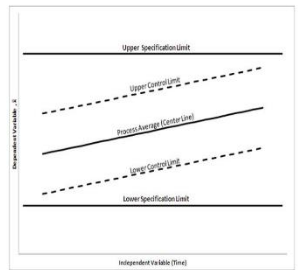


Fig (1.1): Conventional control chart **Fig (1.2): Regression control chart**

The construction of regression control charts became a popular control chart after Mandel's [1969] contribution to solving the postal management problems of studying man-hours used with respect to pieces of mail handled, which was a mandatory requirement for sorting out post mail in 74 post offices of the United States. He applied regression analysis to this historical data and established a regression control chart summarizing the feasibility of adopting less manpower in processing the mail activities. Since the regression control charts are used in complex situations where the conventional charts fail to serve. It is assumed that the response variables are normally and independently distributed for each specific regressor, with a mean value estimated from the regression line and the respective standard error. There exist many challenges in the use of regression control charts. Researchers like Gani, Chen, Sentruk, Erginel, etc addressed the challenges, and still, it needs to address many more challenges. Because of the culmination of two concepts, the traditional control charts, and regression control charts, the study must be lined up and organized for a better understanding to meet the challenges not addressed by the researchers.

Regression models are used to find the relationship between a dependent variable and one or more independent variables based on classical assumptions namely,

1. The linear relationship-A linear relationship implies that a change in a reaction y as a result of a one-unit change in $x1$ is constant regardless of $x1$'s value.

2. No autocorrelation- The influence of $x1$ on y is independent of other factors, according to an additive relationship. The residual terms should not be related in any way autocorrelation is the absence of this phenomenon.

3. Homoscedasticity- Homoscedasticity occurs when the variance of the error terms is constant.

4. No multicollinearity. The absence of multicollinearity occurs when there is a high correlation between the independent variables.

Ragnar Frisch's term multicollinearity helps to distinguish between the several explanatory variables when the assumptions are violated in the regression model. Multicollinearity is a concerning factor as it affects the independent variable's statistical significance and might result in confidence intervals with less credible probabilities. It occurs when there is a linear relationship between two or more predictors or two or more independent variables that are highly correlated. Therefore, a focus on the violation of multicollinearity assumptions is crucial in constructing regression control charts to identify the out-of-control charts at the earliest and achieve the targeted quality of the product consistently. In the following section, a discussion on the construction of regression control charts in the presence of multicollinearity in the observed data is presented.

When it comes to the discussion of the regression control chart and its variations, the regression control chart in the presence of multicollinearity has provoked the need for the research survey. Articles worked in this survey focus on regression control charts for a period of 11 years 2010-2021, categorizing the regression control charts with and without multicollinearity. The article is organized as follows: Section I contains the introduction about the control charts, Section II describes the survey of articles according to content review based on linear, nonlinear, and generalized regression, and Section III consists of the discussion and conclusion about the survey done on regression control charts.

II. SURVEY OF ARTICLES

Each of the articles reviewed is based on regression control charts, which cannot be generalized to a special field of study. These charts are so widely used in practice that there exists no limited scope for their application. To summarize these studies for a duo decennial period of time, a literature survey has been carried out and the following details are obtained to understand the varied features and details of the study.

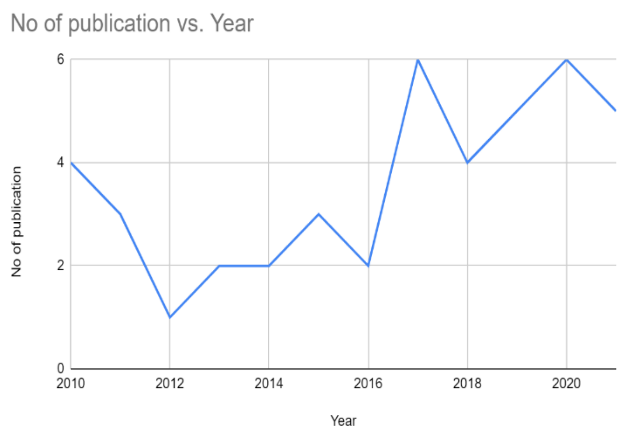


Fig 2: A bird's view of articles based on various regression control charts published during 2010-2021.

Figure 2 shows the number of articles reviewed during 2010-2021 and shows the status of the research work carried out on regression control charts. The study and status of the researcher presented below will help the researcher, particularly the budding researchers, to identify and focus on the research problems that are important and not addressed in the literature.

2.1 Survey of literature

2.1 Regression Control Charts based on Linear Regression Model

The RCC described by W.Gani, H Taleb, and M Limam (2010) is based on a support vector regression model that utilizes the SVR-supervised statistical learning technique. With regard to the ARL criteria, the SVR-Chart has been shown to perform better than conventional least square and partial least square approaches in terms of SDEP and SEP. The SVR chart has been acknowledged as the robust chart in process control to eliminate residuals. The model's performance is positive and has been evaluated using a set of cascade process data with nine input variables. Instead of linear SVR-based residual control charts, the use of linear fuzzy RCC based on alpha cut approximation theory has been clarified. In contrast to linear SVR-based residual control charts, linear fuzzy RCC is based on alpha-cut approximation by S Senturk's (2010). The author demonstrates why it is more appropriate than the conventional RCC by outlining the theoretical framework used to examine how the inner diameter of the natural gas valve varies. When the population characteristics are known, a novel fuzzy standard deviation method with a real dataset from a biscuit factory is utilized to connect fuzzy sets of $\bar{x}$ and s control charts. The outcome that is so achieved has been proven to be flexible with respect to both the upper and lower control boundaries by N Ergniel along with Sentruk N (2011). In order to monitor the experimental data and estimate the stress-strain curve B Özkul and AD Karaoğlan (2011) have explained a case study with the initial tangent and young's modulus values using the RCC. In order to determine Young's modulus, which correlates to the values computed using analytical approaches, authors have justified their study effort with SPC charts. The experiment uses six cube specimens and six-cylinder specimens to cast the results. Z Jianlan and M Yizhong (2011) have introduced studentized residual EWMA control charts, which are dimension-free, and suggest a multistage correlation procedure for modest changes. Different smoothing settings are used to test the effectiveness of the chart using ARL, and it is reported that the charts are pretty excellent. Regression modeling and recurrent neural networks have been integrated to validate the variable process control chart. With an accuracy rate of 89.47%, R Behmanesh and I Rahimi's (2012) model has been effective enough for forecasting. The RNN was optimized using the design of the experiment. They have shown their approach using data from Esfahan Oil Refining Co. (EORC). R Peñabaena Niebles, O Trespalacios et al (2013) have compiled a body of knowledge on the design of control charts based on auto correlated data during the past 20 years of research, addressing three issues: residual-based control charts, model-based control charts, and data mining approach giving a drastic motivation for researchers to continue further with varied approaches. The RCC, which has advantages over statistical quality control diagrams, is the subject of İ Özdamar (2013). Diagrams are insufficient to depict statistical quality control during periods of rising or falling processing time is what the author concludes by a case study.

When the observations rise with regard to time, AD Karaoglan, M Bayhan (2014)have presented a novel regression control chart (NRC) for an auto-correlated process to detect shifts in the production process. Utilizing the AR (1) model created by the NRC aids in monitoring the process' progress along with monitoring samples. The simulation study is conducted to check the performance using average run length and average correct signal rate. The conventional control charts have shown to be inadequate for analysis since the advent of p and np charts based on constant sample size and variable sample size, respectively. This inspired N Erginel in 2014 to suggest p and np charts based on fuzzy rules for capturing ambiguity. The suggested charts assist in identifying judgments that are "somewhat in control" and "out of control". In this paper, FS Souzaa, DC Pedrini, et al (2015) goal is to offer control charts for capacity indices based on regression models for symmetric and asymmetric specifications, followed by a comparison with the conventional capability indices. The need of applying capacity indices was emphasized by the authors, who also noted that using traditional indices for the procedure might lead to inaccurate findings. Based on sample statistics, a novel control chart for mean process monitoring is presented by M Azam, A Arshad, et al (2017) for two consecutive occurrences. ARL is calculated for both in-control and out-of-control mean shifts, and it is then contrasted with conventional and EWMA control charts to see how well they performed overall. When the procedure is changed, the suggested chart performs better. Milk yield data from a rural location in Punjab is taken into consideration for the purpose of full analysis and is shown to be effective for a single sampling chart for two subsequent occasions based on day-by-day production that can handle data in bulk. Although there is a wide area of research, Şentürk and J Antucheviciene in 2017 have developed an interval type -2-fuzzy control c chart for the number of non-conformities, and their application to the food industry justifies its performance. The proposed concept helps to frame a theoretical structure. The application study takes place for a food company in turkey leading to the process package being "in control". F Hayati (2017) has established that the regression control chart as a trustworthy tool for process analysis and quality improvement for two connected variables. Regression control charts are often used in a variety of fields, including healthcare, research, and the service sector. The quality of an aged care facility, the length of the insurance policy application procedure, and the cost of items provided by a corporation are three case studies on which the author has worked. As a result, the regression control chart used in this study is a useful tool for incorporating the permitted variance from the other sources. The suggested control chart by Y Chen and T Hanson (2017) merges the regression model with the traditional control chart for Transformed Bernstein Polynomial Prior to inheriting the smoothness property, the authors' technique is ideally suited for the screening process for big data sets. The research suggested by J Pérez-Rave, L Muñoz-Giraldo (2017) about a brand-new class of variables for tracking financial processes in auto-correlated processes, dubbed financial variables. For the scaled residuals at various regression stages, three charts—the individual chart, the CUSUM chart, and the EWMA chart—are built. Control charts are anticipated to be significant in the field of process monitoring and control.

T Mahmood, M Riaz, et al (2018)study compares the proposed Max-Exponentially Weighted Moving Average -3 and SS-EWMA-3 control chart to the EWMA/R chart, HotellingT-2 chart, Shewhart 3 chart, and EWMA _3 chart. The average run duration and additional quadratic loss, sequential extra charts are used to assess the performance metrics of these charts. It is shown that the suggested chart performs better. Chemical industries' chemical gas sensors are used for a practical illustration. N Erginel, S Şentürk et al (2018] are the first to introduce the interval type-2 fuzzy p-control chart. Because interval type-2 fuzzy sets have more uncertainty while establishing membership functions, interval type-2 fuzzy fraction nonconforming numbers were thought to manage more uncertainty in the process in this research. In a real-world application, a firm that makes ceramic tiles uses the created fuzzy control chart for interval type 2 fuzzy p charts. The improved scaled weighted variance S control chart (SWV-S) proposed by K Yimnak and R Intaramo (2019) to upgrade into a fuzzy scaled weighted variance S chart (FSWV-S) is discussed. Here, utilizing a new S Control chart, the goal is to investigate the skewed population of process dispersion. The effectiveness of the chart is assessed using ARL through simulation. AA Yazdi, AZ Hamadani, et al (2019) study uses the MEWA control chart, MEWA/2 Control chart, and MEWA 3 Control chart as its three methods for checking the

MSL profile. Regarding AARL, SDRL, and CVARL, the performance of these charts is examined for both in-control and out-of-control conditions. In some cases, MEW performs well in the control state, but the best CVARL measure is used for comparison due to the usage of both AARL and SDARL.T Abbas, T Mahmood, et al (2020) investigate two configurations, namely the classical (Shewhart, CUSUM, and EWMA) and Bayesian, with an emphasis on Neoteric Ranked Set Samples (NRSS) for linear profile monitoring. Finally, a thorough simulation study is carried out. The authors have demonstrated that in this instance, both the perfect and imperfect NRSS Bayesian control charts outperform the traditional control charts. A comparison of the maximum entropy and linear regression principles is made, and it is discovered that the maximum entropy principle is a reliable technique for spotting discrepancies in the analysis of data with modest changes in the pharmaceutical industry by AF Mortezanejad, GM Borzadaran, et al (2020). Performance measures for comparison include the average run length, mean of false alarm (ARL0), and average delay time -mean delay of real alarm time (ARL1).Using Hotelling's T2 and SPE Control charts to spot mean shifts in the response, F Centofanti, A Lepore, et al (2021)have studied the idea of FRCC. The suggested chart has been evaluated using a genuine case study of the shipping sector to determine CO2 emission reduction, and results have shown that the FRCC performs better than its rival control charts, particularly the response and Index -based control charts in terms of the ARL. The authors H Wen, L Liu, et al (2021) suggest using a Poisson process Regression adjusted EWMA control chart to track small changes. The simulation research and the hospital's data set on influenza are utilized to assess the performance of the chart. Performance testing is conducted using the ARL function. The intended control chart will be used to update and correct the model being investigated over time. By creating Shewhart, EWMA, and CUSUM charts based on Ridge deviance residuals for Poisson and COM-Poisson profiles, U Mammadova, MR Özkale (2021) deal with strongly correlated variables. The effectiveness of COM Poisson Control Charts is supported by a simulation study and a real-world case with plastic plywood. The number of faults per sheet of laminated plastic plywood with shrinkage, assembly time and other factors are studied for plastic plywood as a dependent variable.

2.2 Regression Control Charts based on Non-Linear Regression Model

The multivariate nonlinear auto-correlated processes have been proposed by IB Khedira, C Weihs, et al(2010) utilizing a non-parametric technique termed SVR-based Control Charts. According to their research, SVR-COT and SVR-EWMAT charts outperform ANN and SVR control charts for longer shifts. The authors reflect their study on multivariate nonlinearity and solely for auto-correlated systems when compared to Gani [2010]. This can be a variant of residual control charts based on SVR. Control charts have been developed by R Garthoff, I Okhrin et al (2015) to simultaneously track the means and variances of multivariate nonlinear time series. The distance between these observed variables and the goal values is determined using the Mahalanobis distance measure. To evaluate the effectiveness of the proposed techniques, a simulation study is conducted. Performance is measured using the average run length. In order to identify changes in the process mean vector, Hwang (2016) has developed a multi-output least squares support vector regression and utilized it to construct a residual multivariate cumulative sum control chart. The multi-output least squares support vector regression-based control chart that is recommended yields more encouraging findings in terms of spotting minute changes in the process mean vector. Because of this, the author asserts that the MCUSUM is effective. To examine the temporal profile of linked line segments, a Case study-based regression spline control chart has been created by John, V Agarwal (2019). The technique is used to track the client servers' response times for an IT firm, producing a successful outcome. The water quality data is checked using an MCUSUM control chart by H Khusna, and M Mashuri (2019) against the mean vector of time series data on the MLS-SVR model's residuals. ARL is a technique used to evaluate performance. The study's exclusive focus has been on auto-correlated data.

2.3 Regression Control Charts based on Generalized Regression Model

J Yu & J Liu (2010) suggested a probability control chart based on logistic regression (LR) in the research to improve process monitoring and to depict process change for autocorrelated data. Their LR Probability chart's performance is tracked using the ARL index. This is another version of auto-correlated production procedures for qualitative work. H C Ong, E Alih (2015)uses a cluster regression control chart (CRCC) in a multivariate context for the Hotelling T2 multivariate Control Chart for potential outliers; however, this approach has been shown to be rather unreliable when the sample size of the data level exceeds 40% of data contamination. Both the outlier and the estimator have been found using the Bacon forward search algorithm. To validate the study, a real-world dataset of pulp fibre is used along with a Monte Carlo simulation. D Marcondes Filho, AMO Sant'Anna (2016) tracked count data using both Poisson regression and principal component analysis. Wherein a PCA is used to convert correlated data into uncorrelated ones. First, Poisson model-based control charts are generated, then PCA, and finally, PPCR-based r-control charts. Based on a simulation analysis and a case study of the manufacturing of plastic plywood, the authors' novel strategy has been shown to be superior. Shrinkage, assembly time, wood density, and the drying temperature are used as independent factors in the research of plastic plywood while the number of faults per laminated plastic plywood is used as a dependent variable. Y Chen (2017) has demonstrated that when the mean shift is of minor size and is represented in a first-order autoregressive model, the EWMA chart beats the X bar chart. An actual example of the quarterly gross domestic product of three nations is used to study and support the properties.

Control variables taking the form of fractions and proportions, a beta regression control chart (BRCC) is presented by FM Bayer, CM Tondolo, et al (2018). When the mean and dispersion are impacted by control variables, beta control charts—which serve as a basis for beta regression control charts—are generated. In terms of average run duration, the proposed BRCC is compared with RCC and BCC using databases that contain data on the tyre manufacturing process and air humidity, resulting in a smaller length and higher sensitivity for BRCC. For identifying the shift, a multi-output least square support vector regression (LS-SVR) based residual control chart is provided by H Khusna,M Mashuri, et al (2018), followed by a multi-output LS-SVR based MCUSUM control chart for the process mean vector. Nonlinear relationships between the variables are addressed using an auto-regressive process control chart. When compared to other charts, the multi Output LS-SVR performs better at spotting minor shifts. Performance is assessed using the average run length. R Fazai, M Mansouri et al (2019) offer a strategy for water distribution network leak/contamination detection using a generalized likelihood ratio (GLRT). Simulation research is done to demonstrate that the MSGPR-EWMA-GLRT technique is superior to the MSGPR-based GLRT method in the case of SVR and GPR-based GLRT. This is done to assess the performance of the EWMA-GLRT chart. Gaussian distribution to analyse the crop production data from Nigeria to comprehend and investigate the assignable cause variation in the Federal Capital Territory (FCT) has been studied by OT Arowolo, MI Ekum (2020). An exploratory data analysis of the charts leads to the conclusion that crop production and four other independent variables are related. The model emits an alert in response to any production variance. S Kinat, M Amin et al (2020) suggest a control chart based on a generalized linear model (GLM) for situations where the response variable has a distribution belonging to the exponential family called the inverse Gaussian distribution. In most cases, the response variable is assumed to follow a Normal distribution; however, in this paper, the IG distribution is proposed, and the data model under GLM is based on data-based (Y-IG), Deviance residual (DR-IG), and Pearson's Residual (PR-IG) for Inverse Gaussian. The Performance measures are validated using the Average Run Length, Standard Deviation of Run Length, and Median of the Run-length. By using a real-world example of the textile industry manufacturing yarn with Count Lea Strength Product (CLSP) as the dependent variable and Micronaire (MC) as the independent variable, the study's validity is tested.

IBRCC is suggested for intervals of [0,1] or [0,1] to check the quality features by LMA Lima-Filho, TL Pereira, et al 2020). Run length was used as a comparative parameter in simulation research that used actual public administrative data to validate the efficiency of the towns. The findings show that IBRCC may be employed by disregarding the explanatory variables in place of applying an incorrect Regression model for the control chart. The mean absolute percentage error, standard deviation run length, and median run length are used to assess performance. The Principal Component Analysis (PCA), Functional PCA, GLM with Probit and Logit functions, and Neural Network are all presented by JM Kim, N Wang et al (2020).The residual control chart for binary data is created using the regression model together with the input variables for non-symmetric data dealing with multicollinearity. The suggested graphic uses multivariate data that is both highly dimensional and often occurs. To validate the suggested approach, simulation research is carried out alongside real-world cancer data. A Jamal, T Mahmood (2021) demonstrates that for small shift sizes for crash data, the EWMA Type control chart performs better than the CUSUM control charts and Shewhart control chart. COM Poisson Regression, based on the COM-Poisson model Using ARL and ADRL serving as performance metrics, control charts with EWMA and CUSUM charts are proposed. A comparison is made between an EWMA chart for deviance residuals and an EWMA chart for Pearson's residual. The findings are fitted to the GLM. This is justified using actual data on the mortality rate of children, and the performance of the negative binomial distribution is validated using the ARL approach by S García-Bustos, N Cárdenas-Escobar, et al (2021).

Performance evaluation of control charts

The Average Run Length (ARL) is commonly used to measure the performance of control charts instead of the usual α and β errors used for testing hypothesis. The number of samples taken before a signal is detected is referred to as the run length. The length of the run is a random variable with only integer values. To evaluate performance, the predicted value or average run length is utilized. Researchers proposed utilizing more reliable measurements to overcome the ARL's weakness as the sole measurement of a control chart's performance. The 50th percentile of the run length distribution is Median Run Length (MRL). It refers to the median number of samples drawn on a control chart before an out-of-control signal is issued. Similar to these lines researchers have used Standard deviation run length(SDARL).Coefficient of variation of Average Run length(CVARL).SDARL and CVARL are used to evaluate the in-control and out-of-control performance of control chart schemes.

III. DISCUSSION AND CONCLUSION

In this paper an extensive survey of the regression control chart is conducted from 2010-2021. Articles from prime journals are taken into consideration and a few of them are not included in this survey, since they do not fall within the scope. Each author addressed in this paper has done an in-depth study in their area of interest with valid and outstanding real-life examples that have been executed and proved to be the efficient/ robust method for each of their simulated as well as real-life data. The findings of these authors are all published in leading journals and have wide scope for further research. It is noticed that the proposed regression control charts are widely used in many fields of study like Industry, Health care, Agricultural, Manufacturing, and many more. The focus on kernel method provide by the Gani (2010) in support vector regression based residual control chart gives a clear technique which can be adapted to visualize further studies in terms of various dimensions and to analyze the relationships between measured and latent variables. IB Khedira et al (2010) has also worked with support vector regression for multivariate nonlinear auto correlated process for detecting large shifts. The formulation of Fuzzy $\bar{x}$ and R regression control charts by Senturk in 2010 for alpha cut approximation helps to study basic tool wear problems and monitors the deviations with respect to in control and out of control .An extension of the same work by Erginel,et al in 2011 towards a new fuzzy standard deviation control charts when the population parameters are known gives an easy way for the calculation of application purpose further extension to the same work in 2014 for attribute control charts have contributed vastly to the field. Senturk and Jurgita's interval type 2 fuzzy c-control chart basically focuses the researchers when the data is of type-2 fuzzy number, followed by type 2 fuzzy p-control chart by N Erginel et al(2018) exploring for more suitable applications. Young's modulus used in the study for stress–strain curve for Regression control charts rises from a linearity to a second order polynomial which in fact is an effective and an alternative way used instead of analytical method which is presented in Ozkul Case study. Reza and Iman's (2012) integration of recurrent neural network with regression has proven to be an efficient model with respect to forecasting producing good accuracy .The new Regression control chart proposed by Aslan et al(2014) for auto correlated helps the researchers in understanding the process progress .When there exists high correlation over two successive occasion of time the author Muhammad Azam et al (2016) work on the proposed model for homogeneous data is relatively new when compared to literatures available for the same. F Hayati's (2017) case studies helps the researchers of similar interest to work towards regression control charts. J Pérez-Rave et al (2017) study on transport logistic has proved that financial variables are of importance for auto correlated data providing a new horizon for research. Implementation of control charts in simple linear profiles provides an insight to progress several others works of nonlinear /multiple as per Tahir Mahmood et all(2018). Several other authors' discussion has always enriched the work in regression control charts say it may be linearity or nonlinearity cases.

Most of the Performance evaluations are done using the Average Run Length (ARL) and Standard Deviation Run length (SDRL). This doesn't mean that other evaluation metrics are not of importance. Some authors have used metrics like (AADRL, SDARL, CVARL, etc. as the efficiency measures and studied the robustness of the control charts. The idea of control chart application only in a few fields will be ruled out by critically knowing the various fields used by different authors for their proposed control charts. The survey paper will help the researchers to know the status of existing Regression control charts and to propose new control charts by considering the other factors that are not addressed in the literature and are challenging.

Acknowledgements The authors would like to thank the anonymous referees for their insightful remarks and recommendations.

Funding Not applicable

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Author contribution Statement

The authors confirm contribution to the paper as follows: study conception, design of the work, analysis, interpretation and draft manuscript preparation: Nancy, M; Study conception and Critical revision of the article: Dr. Hemlata Joshi, Dr. B.V. Dhandra. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

[1] Abbas, T., Mahmood, T., Riaz M., & Abid, M: "Improved linear profiling methods under classical and Bayesian setups: an application to chemical gas sensors". Chemometrics and Intelligent Laboratory Systems, 196, 103908(2020).
[2] Ahmadi Yazdi, A., Hamadani, A. Z., & Amiri, A: "Phase II monitoring of multivariate simple linear profiles with estimated parameters". Journal of

Industrial Engineering International, 15(4), 557-570(2019).
[3] Alwan, L. C., & Roberts, H. V: “Time series modeling for statistical process control”. Journal of Business and Economic Statistics, 6(1), 97-95(1988).
[4] Arowolo, O. T., & Ekum, M. I: “Generalized Regression Control Chart for Monitoring Crop Production”. American Journal of Theoretical and Applied Statistics, 9(4), 90-100(2020).
[5] Azam, M., Arshad, A., Aslam, M., & Jun, C. H: “A control chart for monitoring the process mean using successive sampling over two occasions”. Arabian Journal for Science and Engineering, 42(7), 2915-2926(2017).
[6] Bayer, F. M., Tondolo, C. M., & Müller, F. M: “Beta regression control chart for monitoring fractions and proportions”. Computers and Industrial Engineering, 119, 416-426(2018).
[7] Behmanesh, R., & Rahimi, I: “Using combination of optimized recurrent neural network with design of experiments and regression for control chart forecasting”. In Business Engineering and Industrial Applications Colloquium (Vol. 1, No. 1, pp. 435-439) (2012, January).
[8] Capezza, C., Centofanti, F., Lepore, A., Menafoglio, A., Palumbo, B., & Vantini, S: “Functional regression control chart for monitoring ship CO 2 emissions”. Quality and Reliability Engineering International 38(3),1519-1537(2022).
[9] Chen, Y., H : “EWMA control charts for multivariate auto correlated processes”. Statistics and Its Interface, 10(4), 575-584(2017).
[10] Chen, Y., & Hanson, T: “Semiparametric regression control charts”. Journal of Statistical Theory and Practice, 11(1), 126-144(2017).
[11] Dipaola, P.P: “Use of Correlation in quality Control”, Industrial Quality control, 1(1), 40-44(1945).
[12] Erginel, N: “Fuzzy rule-based $\tilde p $ and $ n\tilde p $ control charts”. Journal of intelligent & fuzzy systems, 27(1), 159-171(2014).
[13] Erginel, N., Şentürk, S., & Yıldız, G: “Monitoring fraction nonconforming in process with interval type-2 fuzzy control chart”. In Advances in Fuzzy Logic and Technology 2017 (pp. 701-709). Springer, Cham (2017).
[14] Erginel, N., Sentürk, S., Kahraman, C., & Kaya, I: “Evaluating the packing process in food industry using fuzzy and [stilde] control charts”. International Journal of Computational Intelligence Systems, 4(4), 509-520(2011).
[15] Fazai, R., Mansouri, M., Abodayeh, K., Puig, V., Raouf, M. I. N., Nounou, H., & Nounou, M: “Multiscale Gaussian process regression-based generalized likelihood ratio test for fault detection in water distribution networks”. Engineering Applications of Artificial Intelligence, 85, 474-491(2019).
[16] Gani, W., Taleb, H., & Limam, M: “Support vector regression based residual control charts”. Journal of Applied Statistics, 37(2), 309-324(2010).
[17] García-Bustos, S., Cárdenas-Escobar, N., Debón, A., Pincay, C: “A control chart based on Pearson residuals for a negative binomial regression: application to infant mortality data”. International Journal of Quality & Reliability Management (2021).
[18] Garthoff, R., Okhrin, I., & Schmid, W: “Control charts for multivariate nonlinear time series”. REVSTAT, 13(2), 131-144(2015).
[19] Hayati, F: “Regression control chart for two related variables: a forgotten lesson”. International Journal of Modelling in Operations Management, 6(4), 262-279(2017).
[20] Hwang, C: “Multioutput LS-SVR based residual MCUSUM control chart for autocorrelated process”. Journal of the Korean Data and Information Science Society, 27(2), 523-530(2016).
[21] Jamal, A., Mahmood, T., Riaz, M., & Al-Ahmadi, H. M: “GLM-based flexible monitoring methods: An application to real-time highway safety surveillance”. Symmetry, 13(2), 362(2021).
[22] Jianlan, Z., & Yizhong, M: “Studentised residual-based EWMA control charts”. In 2011 2nd International Conference on Artificial Intelligence,Management Science and Electronic Commerce (AIMSEC) (pp. 3361-3364).IEEE(2011,August).
[23] John, B., & Agarwal, V: “A regression spline control chart for monitoring characteristics exhibiting nonlinear profile over time”. The TQM Journal (2019).
[24] Karaoglan, A. D., & Bayhan, G. M: “A regression control chart for auto correlated processes”. International Journal of Industrial and Systems Engineering, 16(2), 238-256(2014).
[25] Keats, J. B., & Montgomery, D. C. (Eds.): “Statistical process control in manufacturing”. Milwaukee, Wisc(1991).
[26] Khediri, I. B., Weihs, C., & Limam, M: “Support vector regression control charts for multivariate nonlinear autocorrelated processes”. Chemometrics and Intelligent Laboratory Systems, 103(1), 76-81(2010).
[27] Khusna, H., Mashuri, M., Suhartono, S., Prastyo, D. D., & Ahsan, M: “Multioutput least square SVR-based multivariate EWMA control chart: The performance evaluation and application”. Cogent Engineering, 5(1),1531456(2018).
[28] Kim, J. M., Wang, N., Liu, Y., & Park, K: “Residual control chart for binary response with multicollinearity covariates by neural network model”. Symmetry, 12(3) (2020).
[29] Kinat, S., Amin, M., & Mahmood, T: “GLM-based control charts for the inverse Gaussian distributed response variable”. Quality and Reliability Engineering International, 36(2), 765-783(2020).
[30] Lima-Filho, L. M., Pereira, T. L., Souza, T. C., & Bayer, F. M: “Process monitoring using inflated beta regression control chart”. Plos one, 15(7),e0236756(2020).
[31] Mahmood, T., Riaz, M., Hafidz Omar, M., & Xie, M: “Alternative methods for the simultaneous monitoring of simple linear profile parameters”. The International Journal of Advanced Manufacturing Technology, 97(5), 2851-2871(2018).
[32] Mammadova, U., & Özkale, M. R: “Profile monitoring for count data using Poisson and Conway–Maxwell–Poisson regression-based control charts under multicollinearity problem”. Journal of Computational and Applied Mathematics, 388, 113275(2021).
[33] Mandel, B. J: “The regression control chart”. Journal of Quality Technology, 1(1), 1-9(1969).
[34] Marcondes Filho, D., & Sant’Anna, A. M. O: “Principal component regression-based control charts for monitoring count data”. The International Journal of Advanced Manufacturing Technology, 85(5), 1565-1574(2016).
[35] Mortezanejad, A. F., Borzadaran, G. M., & Gildeh, B. S: “Profile control chart based on maximum entropy”. ArXiv preprint arXiv:2012.14289 (2020).
[36] Ong, H. C., & Alih, E: “A control chart based on cluster-regression adjustment for retrospective monitoring of individual characteristics”. PloS one, 10(4), e0125835(2015).
[37] Özdamar, İ.: “The regression control chart and a case study”. Turkish Journal of Forestry, 14(2), 134-137(2013).
[38] Özkul, B., & Karaoğlan, A. D: “Regression control chart for determination of Young’s modulus: A case study”, (2011).
[39] Peñabaena Niebles, R., Oviedo-Trespalacios, Ó., Vásquez Cabeza, J. G., & Fernández Cantillo, L. M: “Diseño estadístico de cartas de control para datos autocorrelacionados”. Ingeniería y Desarrollo, 31(2), 291-315(2013).
[40] Pérez-Rave, J., Muñoz-Giraldo, L., & Correa-Morales, J. C: “Use of control charts with regression analysis for autocorrelated data in the context of logistic financial budgeting”. Computers & Industrial Engineering, 112, 71-83(2017).
[41] Prastyo, D. D., Khusna, H., Mashuri, M., Suhartono, S., & Ahsan, M: “Multivariate CUSUM control chart based on the residuals of multioutput least squares SVR for monitoring water quality”. MJS, 38(Sp2), 73-83(2019).
[42] Sentürk, S: “Fuzzy regression control chart based on α-cut approximation”. International Journal of Computational Intelligence Systems, 3(1),123-140(2010).
[43] Şentürk, S., & Antucheviciene, J: “ Interval type-2 fuzzy c-control charts: an application in a food company”. Informatica, 28(2), 269-283(2017).
[44] Souzaa, F. S., Pedrinia, D. C., & Ten Catena, C. S: “Capability indices for control charts based on regression models”. Brazilian Journal of Operations & Production Management, 12(2), 234-247(2015).

[45] Wen, H., Liu, L., & Yan, X: "Regression-adjusted Poisson EWMA control chart". Quality and Reliability Engineering International, 37(5), 1956-1964(2021).
[46] Yimnak, K., & Intaramo, R: "An fuzzy scaled weighted variance S control chart for skewed populations". Thai Journal of Mathematics, 18(1), 53-62(2019).
[47] Yu, J., & Liu, J: "LRProb control chart based on logistic regression for monitoring mean shifts of auto-correlated manufacturing processes". International Journal of Production Research, 49(8), 2301-2326(2011).