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DOCTORADO EN CIENCIAS DE LA INGENIERÍA

ENFOQUE ESTADÍSTICO NO-INVASIVO PARA EVALUAR LA VARIABILIDAD DE LOS PROCESOS CON BASE EN ÍNDICES DE CAPACIDAD DE PROCESO Y GRÁFICOS DE CONTROL DE PROCESO CON DATOS INDIVIDUALES DIFUSOS

Tesis que para obtener el grado de

DOCTOR EN CIENCIAS DE LA INGENIERÍA

presenta: José Luis Rodríguez Álvarez

Director de tesis: Dr. Rogelio López Herrera

Co-director de tesis: Dr. Iván Esteban Villalón Turrubiates

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TÍTULO: **Enfoque estadístico no-invasivo para evaluar la variabilidad de los procesos con base en índices de capacidad de proceso y gráficos de control de proceso con datos individuales difusos**

AUTOR: José Luis Rodríguez Álvarez
Ingeniero Industrial (Instituto Tecnológico de Durango, México)
Maestro en Ciencias de la Ingeniería Industrial (Instituto Tecnológico de Ciudad Juárez, México)

DIRECTOR DE TESIS: Rogelio López Herrera
Departamento de Electrónica, Sistemas e Informática, ITESO
Ingeniero Químico (Universidad de Guanajuato, México)
Maestro en Ciencias en Ingeniería de la Energía (Universidad de Illinois, Estados Unidos de América)
Maestro en Ciencias en Calidad y Estadística Aplicada (Instituto de Tecnología de Rochester, Estados Unidos de América)
Doctor en Ciencias de la Ingeniería Química (Universidad de Illinois, Estados Unidos de América)

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ITESO – The Jesuit University of Guadalajara

Department of Electronics, Systems, and Informatics

DOCTORAL PROGRAM IN ENGINEERING SCIENCES

NON-INVASIVE STATISTICAL APPROACH TO EVALUATE PROCESSES VARIABILITY USING FUZZY PROCESS CAPABILITY INDICES AND FUZZY INDIVIDUAL CONTROL CHARTS

Thesis to obtain the degree of

DOCTOR IN ENGINEERING SCIENCES

Presents: José Luis Rodríguez Álvarez

Thesis Director: Dr. Rogelio López Herrera

Thesis Co-director: Dr. Iván Esteban Villalón Turrubiates

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TITLE: **Non-invasive Statistical Approach to Evaluate Processes Variability Based on Fuzzy Process Capability Indices and Fuzzy Individual Control Charts**

AUTHOR: José Luis Rodríguez Álvarez
Bachelor's degree in industrial engineering (Technological Institute of Durango, Mexico)
Master's degree in industrial engineering (Technological Institute of Ciudad Juárez, Mexico)

THESIS DIRECTOR: Rogelio López Herrera
Department of Electronics, Systems, and Informatics, ITESO
Bachelor's degree in chemical engineering (University of Guanajuato, México)
Master's degree in energy engineering (University of Illinois, USA)
Master's degree in applied quality and statistics (Technological Institute of Rochester, USA)
Ph.D. degree in chemical engineering (University of Illinois, USA)

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To my wife Fabiola, thanks to her patience and understanding this professional achievement has been possible.

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To my Mom, for her full support and always having the right words. Thank you very much for making it possible for me to starting my professional studies when our situation was severely adverse. Thank you Dad whatever you are.

Thanks to my sisters and brothers for always being present and continuous support.

Resumen

El pensamiento estadístico y el registro y seguimiento de la calidad en las características del producto, ya sean estas de tipo variable o atributo, desempeñan un papel fundamental en el éxito de la mejora de la calidad para reducir la variación del proceso o del producto. Para ello, las técnicas de gráficos de control y los índices de capacidad del proceso se utilizan ampliamente en diversas industrias manufactureras y de servicios para llevar a cabo una evaluación global del rendimiento del proceso. Sin embargo, se debe advertir que los resultados obtenidos mediante el uso de éstas técnicas dado que funcionan bajo ciertos supuestos, generalmente presentan variación a través del tiempo, principalmente en procesos complejos en los que es difícil recoger suficientes datos sobre las variables de calidad, y en procesos que presentan incertidumbre en las mediciones. Por tanto, se debe tener especial cuidado en la elección de la técnica adecuada para tener una evaluación cercana a la realidad del proceso. En primer lugar, en esta tesis doctoral se presenta una alternativa de gráficos de control difusos para medidas individuales y de rango móvil basada en el enfoque de rango medio difuso con α-cut. El método propuesto para generar los números difusos se basa en el nivel sigma del proceso, y en la variación observada en cada muestra. Así, estos gráficos de control difuso son más flexibles, ya que la amplitud entre los límites de control superior e inferior es mayor que la mostrada en los gráficos de control tradicionales. En la segunda propuesta, se presenta un método alternativo para estimar los índices de capacidad del proceso bajo un enfoque difuso. Esta alternativa utiliza una aplicación acoplada de modelado + diseños experimentales, que se presentan como un enfoque no invasivo. Este enfoque se utiliza dos veces: primero, para conocer la variabilidad del proceso, y segundo, para reducir la variabilidad de la variable de control de calidad. Cuando se realiza una evaluación del desempeño de procesos basada en gráficos de control e índices de capacidad, es necesario el uso de datos de las variables de calidad de interés. Generalmente, los datos son registrados por el departamento de control de calidad o los instrumentos de medición que forman parte del proceso. En el método propuesto, el conjunto de datos utilizado para evaluar la capacidad del proceso corresponde a valores predichos por un modelo entrenado con una precisión razonable. Esto implica que, además del error del modelo, las medidas incluirán la variabilidad mostrada en cada variable independiente que afecta a la respuesta. El método se validó utilizando un conjunto de datos de peso base real. Los resultados

mostraron que los índices de capacidad de proceso global estimados con el método propuesto, se acercan más a la realidad del proceso que los métodos tradicionales y difusos existentes.

Summary

The statistical thinking and monitoring of the quality of product characteristics, either of a variable or attribute type, plays a key role in a successful quality improvement to reduce process or product variation. For this purpose, the control charts techniques and the process capability indices are widely used in a variety of manufacturing and service industries to carry out an overall evaluation of the process performance. However, it should be noted that the results obtained using these techniques, given that they operate under certain assumptions, generally show variation over time, mainly in complex processes in which it is difficult to collect sufficient data on the quality variables and in processes with uncertainty in the measurements. Therefore, special care must be taken in choosing the appropriate technique to have an evaluation close to the reality of the process. Firstly, in this doctoral dissertation is presented an alternative fuzzy individual and moving range control charts based on the α-cut fuzzy midrange approach. The proposed method to generate the fuzzy numbers is based on the sigma level of the process, and the observed variation in each sample. Thus, these fuzzy control charts are more flexible, because the amplitude between the upper and lower control limits is greater than those shown in the traditional control charts. In the second proposal is presented an alternative method to estimate the process capability indices under a fuzzy approach. This alternative uses a coupled applications of modeling + experimental designs, which are presented as a non-invasive approach. The application has a double purpose: first, to know the process variability, and second, to reduce variability in the quality control variable. When a process performance evaluation based on control charts and capability indices is carried out, it is necessary to use the interest quality variables data. Generally, the data are recorded by the quality control department or the measuring instruments that are part of the process. In the proposed method, the used data set to evaluate the process capability corresponds to values predicted by a trained model with reasonable accuracy. This imply that the measures will include the variability shown in each independent variable that affect the response, in addition to the model error. The method was validated using a real basis weight dataset. The findings showed that the overall process capability indices estimated with the proposed method are closer to the process reality than the existing traditional and fuzzy methods.

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List of Acronyms

ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
CL	Central Limit
CUSUM	Cumulative Sum
DF	Degrees of Freedom
DOE	Design of Experiments
EWMA	Exponentially Weighted Moving Average
FAO	Food and Agricultural Organization
FCCIM	Fuzzy Control Charts for Individual Measurements
FICC	Fuzzy Individual Control Charts
FMRCC	Fuzzy Moving Range Control Charts
GFN	Gaussian Fuzzy Number
GR	Generalized Regression
GUI	Graphic User Interface
ICC	Individual Control Charts
KPI	Key Performance Indicator
LCL	Lower Control Limit
LSL	Lower Specification Limit
MAE	Mean Absolute Error
MAPE	Mean Absolute Percent Error
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MR	Moving Range
MRCC	Moving Range Control Charts
MS	Mean Squares
NN	Neural Network
Non-I FPCA	No-Invasive Fuzzy Process Capability Analysis
PLS	Partial Least Squares
PPI	Pulp and Paper Industry

Pp	Overall Process Capability with Regard to the Variation
Ppk	Overall Process Capability with Regard to the Mean
QCS	Quality Control System
RBF	Radial Basis Function
RMSE	Root Mean Square Error
SE	Standard Error
SPC	Statistical Process Control
SS	Squares Sum
SVM	Support Vector Machine
TFN	Triangular Fuzzy Number
TrFN	Trapezoidal Fuzzy Number
UCL	Upper Control Limit
USL	Upper Specification Limit
VIF	Variance Inflation Factor

Introduction

The development of mathematical models for process optimization must be considered a good process management practice. However, this alternative is not a trivial matter.

In the processes where it is expensive and hard to change process variables, statistical modeling techniques such as regression analysis or artificial neural networks could be an excellent alternative to reduce variability. A model with reasonable precision could work with a robust design of experiments techniques and then set the process conditions that minimize variability in the response variable.

From my own experience as part of the continuous improvement team in the pulp and paper industry in Mexico, it has not been easy to carry out optimization projects based on statistical techniques. The main reason is that the management thinking focuses their efforts on purchasing new technology as a first option to control product quality.

The intensive use of statistical techniques for optimization purposes within industrial processes could be associated with the concept of statistical thinking; therefore, this approach could represent an excellent management alternative to improve a company's capacity indexes and keep quality variables within control, among other problems that may arise. For example, the pulp and paper industry is one of the industrial segments requiring water and energy for its proper functioning. Therefore, according to Lawrence et al. [Lawrence-19b], optimizing their use represents a way to mitigate the emission of greenhouse gases. However, in this doctoral dissertation, only the process control charts and capability indices are addressed as a management practice to improve product or service quality.

These two statistical techniques have been widely used to monitor the quality control variables and measure the process performance. But depending on the characteristics of the measurements, parametric (which we will call traditional) or fuzzy approaches could be used. Since traditional methods assume normality in the data, their verification is fundamental. Therefore, these approaches can be applied if the data follow a distribution with zero mean and constant variance. Otherwise, other alternatives such as non-parametric approaches should be considered [Obaid-21]. On the other hand, in the presence of uncertainty in the process measurements, the fuzzy approach has proven its usefulness to overcome the uncertainty issue

[Şentürk-14]. The results using this approach are shown with a value that indicates the fulfillment level of the statement.

The monitoring of the quality product characteristics, either of a variable or attribute type, plays a key role in a successful quality improvement to reduce process or product variation [Kim-19]. For this purpose, the traditional control chart technique introduced in 1924 by Walter Shewhart has been used in a variety of manufacturing and service industries where the common control charts are based on the sample mean ($\bar{X}$), range (R), standard deviation (s), individual data (X), and moving range (MR) [Mitra-19]. However, the traditional control charts are suitable for well-known and precise data cases; but, as mentioned above in the papermaking process the data usually shows some of these uncertain elements, mainly in the paper moisture content. To overcome the uncertainty problem in the data, accordingly with [Sun-18] the fuzzy set theory represents an alternative. The fuzzy set theory, proposed by Zadeh [Zadeh-65] is used for modeling the data uncertainties of natural language processing and it can be applied in many areas, such as optimization, automatic control systems, information systems, imaging systems, and decision making.

Among many other processes, it is common to find measurement uncertainty in the papermaking process due to its complexity. The papermaking process has multiple variables that affect product quality; however, the basis weight, thickness (caliper), moisture content are main ones [Merbold-16]. Thus, it is important to monitor these variables. Because the complexity of the papermaking process, it is only possible to obtain a single sample of each product; therefore, the type of control char to be used is the individual data.

In the first proposal, an alternative fuzzy control charts for individual measurements are developed for the papermaking process by using the fuzzy individual control charts (FICC) and fuzzy moving range control charts (FMRCC) proposed by Kaya et al. [Kaya-17]. However, unlike this method, the proposed alternative, generates the fuzzy numbers based on the observed variation for the selected time period and the sigma level of the process. This methodology has not been studied nor employed in the papermaking process to control the paper moisture content. This proposed is attractive, because the amplitude between control limits is greater; thus, the control charts can overcome the problem of small shifts in some quality variables due to environmental factors.

On the other hand, another statistical technique is the process capability indices, which is very well defined as the capacity of a process to meet customer expectations defined as specification limits [Kaya-10a]. Process capability indices are summary statistics that measure the process characteristics overall or potential performance (variables or attributes) relative to the target and specification limits [Kaya-10b]. This approach is helpful to define a relationship between the process capacity and the specification limits. This correspondence is made by forming the width ratio between the specification limits and the natural width tolerance set as six process standard deviations units [Montgomery-20]. Because the presence of uncertainty in the measurements; therefore, this statistical technique is also addressed using a fuzzy approach.

In the second proposal, a novelty method is presented to evaluate process performance by non-invasive approach to calculate the fuzzy process capability indices. The proposed method uses the significative process variables data records that have influence in the response. The data collected is used to develop an artificial neural network model. This model is now being employed as data source, firstly applying it into the design of experiments approach to identify the optimal conditions for the process performance. Once the optimal variables operating values had been obtained, these new operating conditions are re-introduced to the neural network model to calculate the output measures. Measures that are being used to calculate the fuzzy process capability indices. At present, in the literature, it is not found an integral method like the one presented.

As mentioned above, the non-invasive approach is introduced to estimate the process capability indices. This approach could be useful for complex processes or for any process where the process optimization using experimental designs is very expensive.

Notice that two conditions are necessary to construct optimal and robust processes. First, it is necessary to have a true cultural change based on the usage of statistical thinking as the first alternative for the process optimization. Second, the management must develop to the human resources on robust statistical thinking.

This document is organized as follows: in Chapter 1 is presented an overview of the statistical thinking approach as a management practice to improve the process capability indices, mainly in the pulp and paper industry where the two proposals were validated. Chapter 2 is focused on modeling + experimental designs as a first implementation of this approach to the parameters optimization in a complex section of the papermaking process. In Chapter 3 are described the building process of the fuzzy individual and moving range control charts, which are based on the

α-cut fuzzy midrange approach. Its performance is compared with traditional individual and range control charts using a real dataset of moisture content measurements. Chapter 4 describes the building process of a basis weight predictive model based on neural networks, until the building process of a graphic user interface (GUI), which can run in a web environment. All this process follows the common procedure of a data science project. The model performance was validated by using an external real dataset not included in the building process. Finally, the Chapter 5 describes the proposed method to estimate the process capability indices under a fuzzy approach. For the modeling + experimental design presented as a non-invasive approach is essential; first, to know the process variability, and second, to reduce variability in the quality control variable. The method performance was validated using a real dataset and comparing its results with the existing traditional and fuzzy approaches.

1. A Statistical Thinking Approach to Improve the Pulp and Paper Industry Capability Indices

In this chapter, a brief overview is presented of what is the pulp and paper industry; as well as the worldwide distribution of production. Although, this is one of the largest industries that impact the environment, some findings show that technology and management practices are the two main approaches being used to mitigate the problem of pollution. A good practice that could help to reduce the strong effect that the pulp and paper industry has on the environment is referred first to get knowledge about the process based on statistical thinking. This approach will allow to achieve a given process capability index and process variability for critical variables. So, in consequence a good quality product could be obtained. In addition, in case that environmental impact exceeds the maximum or minimum allowed by the applicable regulations, the process capability indices should be degraded and affecting the industry performance.

1.1. A Brief Review of Pulp and Paper Industry Production in the World

Ever since paper was invented (c. 3700-3200 BC), it became an essential part of human life [Chakraborty-19]. The pulp and paper industry is a large and growing portion of the world´s economy, its production has increased globally and will continue rising in fact for the next few years [Bajpai-12]. It is expected that India and China will become key countries in this industry growth [Bajpai-14]. In the past decade, the United States and Canada were the leading participants in the pulp and paper industry (PPI). Currently, China is the largest producer of paper, followed by Japan, Germany, Sweden, Canada, and India [Bajpai-15].

Currently, the pulp production leader is the United States, followed by China and Canada. On pulp exportation, Canada comes first, followed by Brazil and United States, and the largest exporters of paper are the United States, Germany and Sweden. World production of paper and paperboard is around 390 million tons, and the sector expect to reach 490 million tons by 2020 [Bajpai-14]. By taking information from the Food and Agriculture Organization of the United

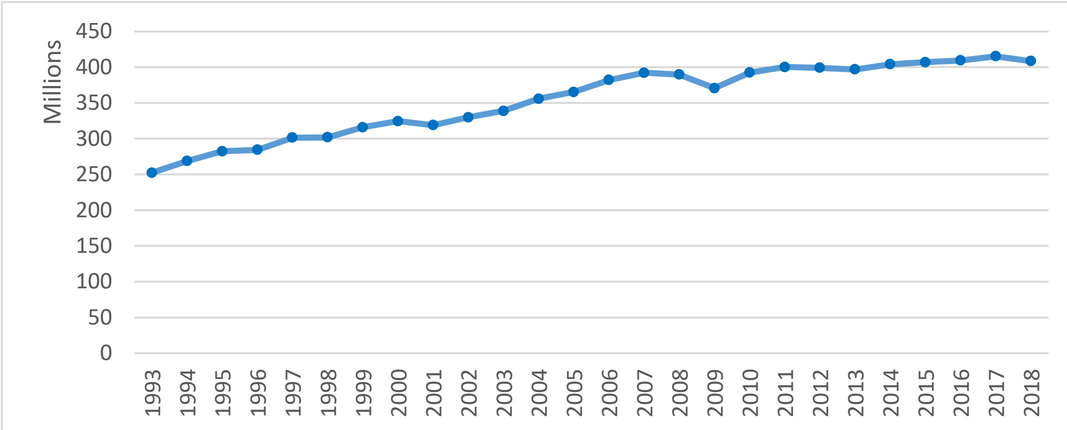


Fig. 1.1 Paper and paperboard production quantity (tonnes) in the world from 1993 to 2018 (taken from [FAOSTAT-19]).

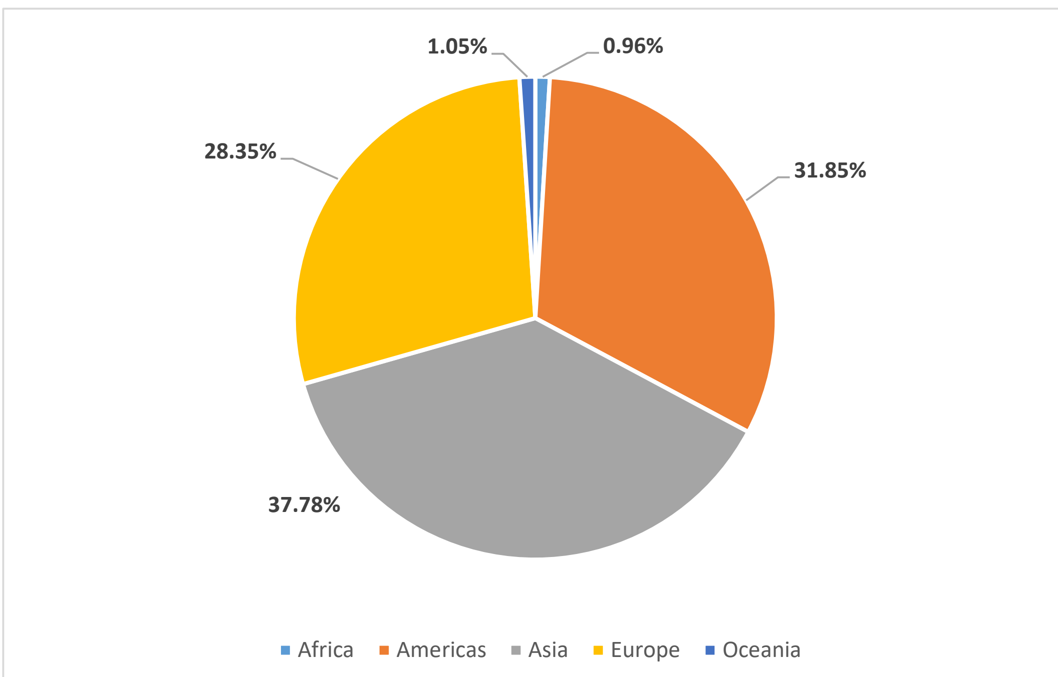


Fig. 1.2 Paper and paperboard production quantity share by region (taken from [FAOSTAT-19]).

Sates (FAO), in Fig. 1.1 is shown the paper and paperboard production in the world. While, Fig. 1.2 shows the paper and paperboard production share by region. Finally, Fig. 1.3 shows the ten main producer countries of paper and paperboard [FAOSTAT-19].

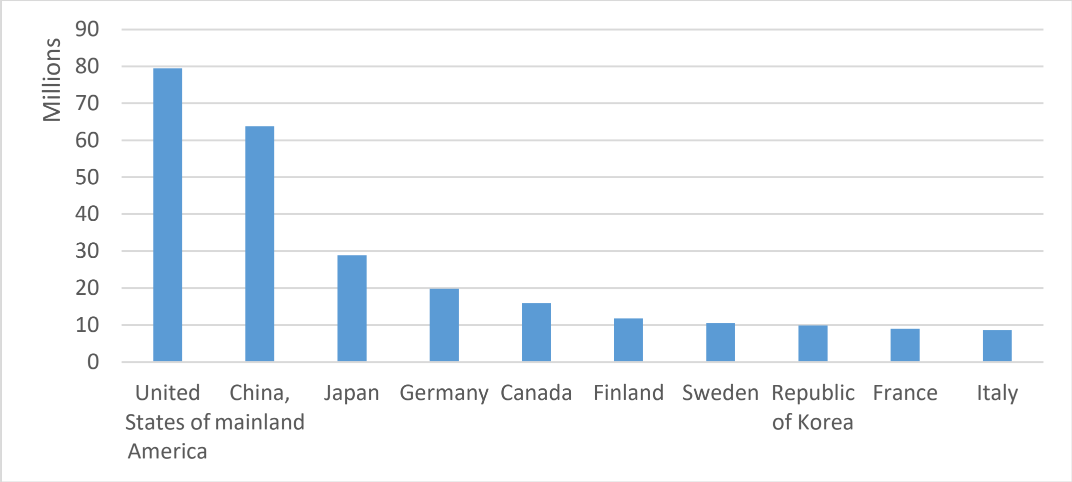


Fig. 1.3 Top ten countries of paper and paperboard production quantity in tonnes (taken from [FAOSTAT-19]).

In other hand, the Asia´s growth is accelerating so rapidly, that its world paper and paperboard production accounts for almost 40% total. Whereas, the European Union and North America accounts around one quarter each. From the 2014 data, the global paper production hit 400 million tons per year first time (ironically the same year that the atmospheric CO2 levels exceeded 400 parts per million). More than half of this WW paper production is consumed between three countries, China (106 million tons), USA (71 million tons), and Japan (27 million tons), with a further quarter in Europe (92 million tons). The entire continent of Africa accounts for just 2% of global paper usage, consuming a mere 8 million tons per year. While, Oceania and Latin America account for around 8% [Haggith-18]. The remaining consumption is distributed among the rest of the countries of Asia and North America.

The FAO statistics indicates that Central America region represents only 6.2% of the total produced by the American Continent in 2018 being Mexico the main producer of Central America with 92.6% (5.5 million tons) of the total. In Fig. 1.4 is shown the annual production in the period from 1993 to 2018. As we can see, the paper and paperboard production in Mexico represents a minimum part of total worldwide production. However, what about process capability performance?, what about pollutant emission?, are people introducing the statistical thinking as an alternative to reduce the process variability and linking this to process pollution?.

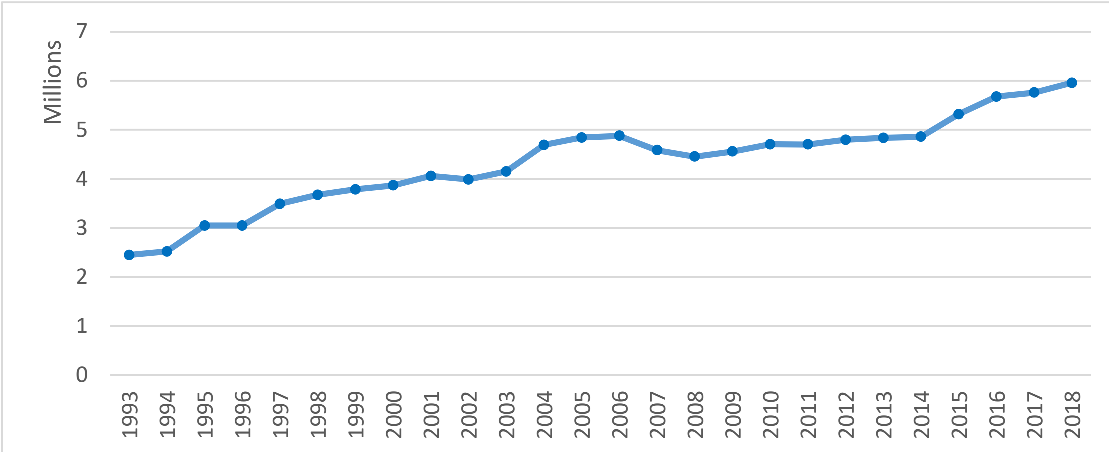


Fig. 1.4 Paper and paperboard production quantity (tonnes) in Mexico from 1993 to 2018 (taken from [FAOSTAT-19]).

1.2. Approaches in the Pulp and Paper Industry to Control Environmental Impacts

Historically pulp and paper industry have been a major pollution sources, discharging to environment gaseous, liquid and solid pollutant compounds. This situation for all types of industries tends to be complex due to numerous factors mainly related to the nature of the process [Tong-18]. For instance, Corcelli et al. [Corcelli-18] mentioned that pulp and paper manufacturing sector constitutes one of the largest industry segment in the world in terms of water and energy usage as well as significant usage and release of chemical and combustion products. While, Lawrence et al. [Lawrence-19b] affirm that this industrial sector accounts for a large share of the world's final energy use, improving its industrial energy efficiency is a way to reduce overall energy use, and in consequence mitigate greenhouse gas emission. For energy intensive industries, the energy efficiency gap has been estimated as being approximately 11%, in which 5% could be decreased through more energy efficient technologies and the other 6% through proactive energy management practices. These percentages are referred to as an extended energy efficiency gap [Backlund-12]. Even, Lawrence et al. [Lawrence-18] mentioned that the pulp and paper industry could have between 5.5 to 19.4% energy savings annually.

As it is described above, two concepts are being considered as the main approaches in the pulp and paper industry to control environmental impacts (as well for other industries). One is referred to the technology use, and other one by the use of management practices. In both cases, optimization is the key concept and being it one of the major objectives.

Companies invests in new technologies or adopt new management practices to optimize the process performance, and as a consequence have greater profitability [Goldratt-84]. Management practices have been considered as the first option to gain profitability; while, technology investment is usually the second option under continuous improvement philosophy.

1.3. Statistical Thinking as Management Practice

The development of mathematical models for process optimization purposes must be considered as a good management practice, although this alternative is not a trivial matter. In the pulp and paper industry, or for any kind of industry where it is expensive and hard to change process variables, the modeling by using statistical techniques as regression analysis or artificial neural networks could be an excellent alternative to reduce variability. A model with reasonable precision could be used to work with robust design of experiments techniques, and then set the process conditions which minimize process response variability.

From my own experience as part of the continuous improvement team in the pulp and paper industry in Mexico, it has been difficult to carry out optimization projects based on statistical techniques. The main reason is because the management thinking focused on the purchase of new technology as a first option. In contrast, the pulp and paper industry has been using statistics optimization methods for more than two decades. For instance, Adamopoulos et al. [Adamopoulos-16] presents a predictive model for the mechanical properties of corrugated base papers (liner and fluting-medium) from fiber and physical property data using multiple linear regression and artificial neural networks, and more closer referred to the paper manufacturing process. Kilulya et al. [Kilulya-15] used a partial least squares (PLS) regression model to evaluate the effects and influence of the lipophilic extractive residues on the quality parameters of dissolving pulp and finding that sterols, fatty alcohol, saturated and unsaturated fatty acids significantly influenced/affected the viscosity, kappa number and carbohydrates in the pulp. While, Marklund et al. [Marklund-98] carried out a multivariate data analysis and partial least squares to model the influence of the fiber properties on strength parameters for softwood kraft pulps made from 20 different types of wood samples.

However, at the moment, the literature does not show any applications in the pulp and paper industry in which the process natural environmental impact is related to some quality control indicator for the critical variables as it could be basis weight and moisture content. Although, closer to this approach, Lawrence et al. [Lawrence-19a] mention that energy management is an important way to improve energy efficiency, but more important would be to say, that quality management could be an important way to minimize environmental impacts of pulp and paper industry or for any other kind of industry, and that its environmental impacts can be determined not only by measuring and comparing defined key performance indicator (KPI), but also through quality control performance indicators.

As a traditional and important chemical industry, the understanding of the whole kind of waste discharged to environment in pulp and paper industry is important and urgent; thus, it is essential that this kind of companies provide the necessary support in terms of how to effectively manage their environmental pollution. Especially in pulp and paper industry, the success of any optimization effort must be evaluated as a result of their environmental pollution impact.

Considered as an alternative within the approach of management practice, the statistical thinking could be an excellent alternative to manage the industry environmental pollution, or almost to reduce process variability and as a consequence to improve process capability indices. In this sense, to construct optimal and robust processes is necessary two conditions. First, it is necessary to have a true cultural change based on the usage of statistical thinking as the first alternative for the process optimization. Second, the management must develop to the human resources on robust statistical thinking.

1.4. Conclusions

There are two main moments in the present work. First, taking advantage of the large amount of data currently provided by the papermaking process, a robust model will be developed to define optimal operating conditions that guarantee some desired process capability indices (*Pp* and *Ppk*). Second, to demonstrate the social responsibility, the process capability indices for any of the two critical quality control variables (basis weight or moisture content) will be affected in a negative way, decreasing its value when environmental impact (water or energy consumption) exceeds the maximum or minimum allowed regulations limits.

It is intended to demonstrate through the future work, that the use of statistical thinking can be seen as a helpful management practice and as an excellent strategy that any industry can take to strengthen the knowledge of the processes and its continuous optimization as well as to collaborate for the care of the environment by reducing process or product variability.

2. Modeling and Parameters Optimization of the Paper Making Processes by Using Regression Tree Model and Full Factorial Design

One of the major challenges in the Pulp and Paper Industry (PPI) is take advantage of the large amount of data generated through their process in order to develop models for optimization purposes, mainly in the papermaking, where the current practice to solve optimization problems is by using the error-proofing method. First, the multiple linear regression technique is applied to find the variables that affect the output pressure that controls the gap of the paper sheet between the rodsizer and spooner section, which is the main cause of paper breaks. As a measure to determine the predictive capacity of the adjusted model, the R^2 and *s* values for the output pressure were considered, while the variance inflation factor was used to identify and eliminate the collinearity problem. Considering the same amount of data available by using machine learning, the regression tree was the best model based on RMSE (*root mean square error*) and R^2 (*determination coefficient*). To find the optimal operating conditions, by using the regression tree model as source of output pressure measurement, a full factorial design was developed. By using an alpha level of 5%, findings show that linear regression and regression tree, found only four independent variables as significant, thus, the regression tree model demonstrated a clear advantage over the linear regression model by improving operating conditions and demonstrating less variability in output pressure. Furthermore, in the present chapter it was demonstrated that the adjusted models with good predictive capacity can be used to design non-invasive experiments and obtain favorable results.

2.1. Introduction

Throughout the history and until the end of the 20th century, it can be observed that the paper industry did not have the same growth shown by some other industries such as the automotive industry. However, the global paper and paperboard production increased in 50% between 1990 and 2006 [Lawrence-18]; thus, giving the first signs of the resurgence of this industry in some countries. The greatest increase in paper and paperboard production is in China from 7% to 16% of the global production, whereas, in some other countries has fallen, for example, in USA, Japan, and Canada. Nevertheless, after 2006 this industry does not have sustained growth due to human consumption habits, supported by technological advances that have pushed back an important industry that has been the national emblem of countries such as Finland [FORBES-18].

In 2013, the global biggest producers of pulp were North America, Europe, Asia, and Latin America, while the most important paper producers were Europe, Asia, North America, and Latin America [S. F. I. Federation-18]. Thus, the economic situation of the Pulp and Paper Industry (PPI) located in traditional manufacturing countries has been uncertain for some time, because of the competition with PPI in countries with plentiful resources, low manufacturing costs, and large newly established production facilities [Leslie-13]. Currently, two new elements are revitalizing it in an unexpected way. First, the boom related to e-commerce, which has notably increased the number of paper and cardboard packaging throughout the world, and the second has been the environmental pressure that encourages the replacement of the plastic packaging that the industry has been using to replace it with a more respectful type of material that may be friendly with the environment.

In Mexico, the Chamber of Paper highlights the importance of this sector, as it asserts that the world production of this industry amounted to 400 million tons in 1999, against all the predictions of the decrease in paper consumption due to the boom in the electronic age [Romero-14]. In addition, technical adaptations and important investments within the production process has changed in last eight years the production way, relying now on methods that do not contaminate, and at the same time recycle the paper that was normally discarded. Therefore, this industry has contributed to develop and structure collection, production, and marketing activities of the waste that is used as material premium within its papermaking processes.

Consequently, the PPI situated in the traditional manufacturing countries has been forced to seek alternatives to be sustainable and profitable [Lawrence-18]. For this purposes, the linear regression technique has been widely exploited in this type of industry.

There are several documented applications of linear regression in different industrial sectors, fields of sciences, and specific areas. For instance, Belusso et al. [Belusso-18] report a new proposal of price by using a multiple linear regression model, including the geographical location of the data center as one variable. Yazir and Sahin [Yazir-17] propose a linear regression approach for Black & Scholes model that is used for call option and put option to derive pricing and risk management. Meanwhile, Herrera and Park [Herrera-14] proposed an early warning model for the global logistics system, which is based on principal component regression that predict a country's global logistics system risk, identifies risk sources with probabilities, and suggests ways of risk mitigation. Muriyatmoko et al. [Muriyatmoko-18] focus their work to quantify how strong correlation impacts h-index towards citations using linear regression. This is to mention a few. Even, accordingly to Kumari and Yadav [Kumari-18] this technique is the most widely used.

In many other applications, the regression models have been compared against other techniques. For instance, Abbas et al. [Abbas-17] developed a mathematical model for predict surface roughness from the experimental data by using regression analysis method, and the experimental data is then compared against the regression analysis and ANFIS (Adaptive Neuro Fuzzy Inference System) estimation. Gul and Guneri [Gul-16] developed two models (regression and neural network) for forecasting patient arrivals at emergency departments with short and long term plans, as well as integrates physical capacity requirements, staffing, budgeting, and arranging staff schedules. While Tsai and Tsai [Tsai-14] present an industrial application of artificial neural network (ANN) and support vector regression (SVR) to diagnose control reflow soldering process in a closed-loop framework.

In applications related to the paper industry, Adamopoulos et al. [Adamopoulos-16] presented a predictive model for the mechanical properties of corrugated base papers (liner and fluting-medium) from fiber and physical property data using multiple linear regression and artificial neural networks. Kilulya et al. [Kilulya-15] used a partial least squares (PLS) regression model to evaluate the effects and influence of the lipophilic extractive residues on quality parameters of dissolving pulp and their findings indicate that sterols, fatty alcohol, saturated and unsaturated fatty acids significantly influenced/affected viscosity, Kappa number and carbohydrates in the pulp. Meanwhile, Marklund et al. [Marklund-98] model the influence of the fiber properties on strength parameters for softwood kraft pulps made from 20 different types of wood samples by using a multivariate data analysis and partial least squares.

Recently, the use of regression trees has been used in many fields of science as smart energy efficient buildings systems [May-Ostendorp-13], construction injury prediction [Tixier-16], wastewater treatment plant performance modeling [Atanasova02], landslide susceptibility studies

[Youssef-16], and data mining [Chrysos-13] to mention a few. Even, in other particular applications scientists has used regression trees to predict the I-V characteristic, create a flood susceptibility map, assess the importance of plant, soil, and management factors affecting potential milk production on organic pastures, assess a wastewater treatment facility compliance with decreasing ammonia discharge limits, estimation of mass first flush ratio in Urban catchments, analyze forest stand damage susceptibility during harvesting, determine the relationship between meteorological factors and mumps, predict overweight trucks from historical weigh in motion data, forecast upland rice yield under climate change [Akbari-19; Bosso-20; Choubin-19; Jeung-19; Shabani-20; Suchetana-17; Zegler-20; Zhang-19a; Zhang-19b].

The theoretical foundations and practical applications of classification and regression trees were first presented by Breiman et al. [Breiman-84]. Classification and regression trees are local regression models, which work in a recursive manner to partition the predictor space by delineating regions where the predictions of dependent or response variable to a set of predictors is homogeneous. These regression tress, first group the predictors and then a particular model is assigned to each of these groupings the simple average is most commonly used [Elith-08]. Local models have the advantage of representing the true relation between the covariates and the response variable in each of the groups in the tree, as compared to global models where a single equation is used for the entire data set. If the response variable is continuous then it is called a regression tree; if categorical then it is called a classification tree [Suchetana-17].

The interpretability of the tree structure is a strong reason for their popularity among the practitioners jointly with good prediction accuracy, fast computation speed, and wide ability, and moreover, a clear advantage of regression trees is that they make no probability distribution assumption, however, identify relevant explanatory variables (or features) and detect interactions among them [Bosso-20].

For years, theory and designed experiments applications were consolidated. In several industries, the contributions of Douglas C. Montgomery and Genichi Taguchi paved the way for routine applications, being this approach one of the strategies that companies have in their improvement projects. When changes are made within the processes, to comply with a quality characteristic, trial and error are usually an alternative. On the other hand, the design of experiments (DOE) approach, where all possible combinations of variables are analyzed by using the factorial design [Box-87]. Finally, the regression tree model is used to describe the response

Fig. 2.1 Rodsizer-spooner section of a papermaking machine.

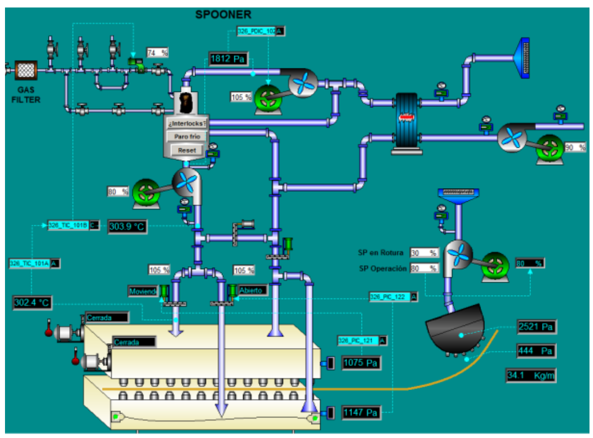


Fig. 2.2 Air box (air tum).

variable and conduct a full factorial design of experiments in order to find the optimal operating parameters.

Although the linear regression and regression trees by using machine learning techniques can be used to try with different kind of problems in the industry, in papermaking process for the rodsizer and spooner section, the use of machine learning has not been exploited.

2.1.1 Problem and Research Objective

Although linear regression techniques have been widely used as described above, in the paper industry, there has been not found any application in the rodsizer and spooner section in a papermaking machine.

One of the common problems in paper manufacturing processes is related to the paper tear offs that occur in different machine sections, mainly between the rodsizer and spooner section shown in Fig. 2.1. The path of the paper in this section is controlled through an air box as shown in Fig. 2.2. The air output pressure must be stable to avoid that the paper undergoes a sudden change in tension causing the paper breaks. Currently, the paper breaks in the rodsizer and spooner section represents an average of 349 minutes per month of machine downtime. Most breaks occur when the paper undergoes through aggressive changes in tension due to the variation in air output pressure (pressure greater than 100 Pa). Thus, the aim of this study is to reduce the process variation below 60 Pa, being this value as a safety factor. In order to find the correct values to reach an air output pressure of 60 Pa, the desirability index will be used to visualize the variability reached after setting the new values in process.

In summary, the present chapter considers the use of the machine learning technique to develop predictive models as a first step, and finally the use of designed experiments for obtaining optimal operating conditions of the parameters. By using this approach, it is possible to reduce variability in the air output pressure, in addition to reduce the economic losses due to machine stoppages related to paper tear offs between the rodsizer and spooner section. Furthermore, if a predictive model can be developed; therefore, a non-invasive design of experiments can be carried out in the process with optimization purposes. This means that the process does not need to be stopped due to the responses of the experiment, because it has been calculated by using the predictive model previously developed. This research approach is useful in papermaking processes if the three next conditions are fulfilled: a large amount of data is available, input and output variables are fully identified, and the process staff have sufficient technical skill level.

2.2. Materials and Methods

Since linear regression technique is widely used in different industrial sectors as described above; therefore, this approach is used firstly to build a model capable of explain the variability of the output pressure as a response of the independent variables shown in Table 2.1. In addition, the present chapter tries to contrast the use of regression tree as an alternative to linear regression technique with aim to evaluate the results and find the best solution (optimal operational parameters conditions) to eliminate the problem of paper tear offs. The section shows the process

TABLE 2.1. VARIABLES OF THE MODEL

Variable name	Variable name on control screen	Coding
Air output pressure	Output Press	y
Differential pressure in dryer 50B	Reg Pres Sec 50B	x_1
Differential pressure in dryer 50	Reg Pres Sec 50	x_2
Differential pressure in dryer 52 54 56	Reg Pres Sec 52 54 56	x_3
Pressure in dryer 50 51	Pres Sec 50 51	x_4
Pressure in dryer 52 54 56	Pres Sec 52 54 56	x_5
Pressure in dryer 53 55 57	Pres Sec 53 55 57	x_6
Steam pressure Line 4	Pres Steam 4 bar	x_7
Steam pressure Line 10	Pres Steam 10 bar	x_8
Internal pressure of air box	Int Pres	x_9

followed from data collection, models development, and design of experiments used to find the optimal operational parameters conditions.

2.2.1 Data Collection

The first task is to identify the main variables (input and output) that affect the paper tear offs. The Table 2.1 illustrates variable names (like to those shown on control screen), units, and codes used for modeling. As a second step, data collection was structured and debugged. The used data, corresponds to one-month period, and cover all the possible operating conditions. The data were extracted from the server. In order to develop a sensitive model to minor changes, data was extracted using one-minute intervals, obtaining initially a total of 40,333 readings. Subsequently, after data debugging, some atypical data from input and output values were discarded, leaving a total of 35,971 readings [Rodríguez-Álvarez-19]. This amount of collected data was used to generate the linear regression model.

2.2.2 Regression Model

The first documented form of linear regression was the method of least squares which was published by Legendre in 1805 [Legendre-1805]. However, it was F. Galton who first introduced the regression term in his work "Regression towards mediocrity in hereditary stature" [Galton-1886].

A linear regression model (LRM) attempts to model the relationship between two or more explanatory variables, as well as a response variable by fitting a linear equation to observe data [Abbas-17]. Considering $x_1, x_2, \dots, x_n$ being a set of *n* independent variables (estimators) associated with a value of the dependent variable *y*, the linear regression model for the *j*-th sample is obtained according to (2-1).

$$y_j = \beta_0 + \beta_1 x_{j1} + \beta_2 x_{j2} + \cdots + \beta_n x_{jn} + \varepsilon \qquad (2\text{-}1)$$

where ε is a random error and β_i $(i = 0,1,2, \dots, n)$ are the unknown regression parameters. A multiple linear regression model (MLR) is fitted by using Minitab.

The least square technique is the used method for the parameters estimation. Least square is a method that adds the squares of the residuals or errors around the regression line to minimize them [Walpole-99]. As suggested by Pulido et al. [Pulido-03] the models are considered highly reliable whether during the sampling process, data do not violate the assumptions as normality, independence, and constant variance. The determination coefficient R^2 is the considered index to select the best model. This index is interpreted as the proportion of total variation in the *y* that is explained by the x_i variables [Wackerly-14]. Since, this research reports a multiple linear regression model, therefore, the adjusted determination coefficient R^2_{adj} is used. This coefficient explains the variability of the model [Acikkar-18], and it is calculated by using (2-2).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - Y_i')^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \qquad (2\text{-}2)$$

where Y_i is a measured value, Y_i' is a predictive value, $\bar{Y}$ is the mean of the measured values, and the number of instances in a test set is given by *n*. The results in analysis of variance will be analyzed considering a significance value of 5%.

In addition, it will be necessary to test collinearity among independent variables. The collinearity problem deals with linear relationships between two or more independent variables. In a linear model as shown in Eq. (2-3), with *n* observations and *p* independent variables, it is supposed that it is correctly specified, the model has mean zero (there is no y-intercept parameter β_0), homoscedasticity and uncorrelated error.

$$Y = X\beta + \mu \qquad (2\text{-}3)$$

If the collinearity is perfect, the correlation coefficient between two independent variables is one, and thus, there is no a unique solution, besides the estimations will be unstable [Garcia-15]. In order to solve the collinearity problem, some authors have suggested the Ridge regression technique [Hoerl-70], the surrogate Ridge model [Jensen-08], the nested regression [Lin-08] among others. A recent approach to deal with this problem was developed by [Piña-Monarrez-11].

On the other hand, by removing variables mechanically can be used to deal with heteroscedasticity and autocorrelation. This approach has been considered for treating the collinearity problem; meanwhile, the variance inflation factor is used to measure it. The VIF index allows to measure the impact of collinearity of the variable x_i, $(i = 1,2, \ldots, p)$ with the rest of the independent variables [Salmerón-Gómez-16]. VIF is calculated from (2-4).

$$VIF_{(i)} = \frac{1}{1 - R_i^2}, \quad i = 1,2, \ldots, p \tag{2-4}$$

where R_i^2 is the coefficient of determination of x_i on the rest of the independent variables. Although multicollinearity should not be a major concern when fitting models with large sets of data, on the contrary, those models should be used for predictive purposes. A variance inflation factor of 5 is an acceptable [De Jongh-15]. In the present research only, variables that have a VIF under 2 were considered [Salmerón-Gómez-16] due to the precision that is required in the paper production process.

When a predictive model is defined, then it is possible to find the operating parameters that allow reducing the variability in air output pressure. This is the main objective and a common interest in all improvements that involve the determination of the optimal setting conditions for independent variables and to attain the best solution for dependent responses [Bera-12]. A frequent practice is to find optimal setting condition by transforming the response to a desirability value. Harrington proposed the first original transformation of a response [Harrington-65]. The desirability index function converts all the desirability values d_j, into a single composite desirability.

The composite desirability is maximized by conventional or unconventional searching techniques. The composite desirability value (D) always lies between 0 and 1. The equation developed by Harrington in 1965 combines the individual desirability with a composite desirability (D) as shown in Eq. (2-5).

$$D = maximize(\prod_{j=1}^{r} d_j)^{\frac{1}{r}} \tag{2-5}$$

where d_j is the individual desirability value.

2.2.3 Regression Trees

As an alternative to traditional linear regression approach, in this chapter is used the supervised machine learning technique with the purpose of train the collected data and try to find a better model than linear regression. Due to the rodsizer section processes all grades of paper, then the regression tree model model can be an excellent alternative. This model has the advantages of not assuming probability distributions and maintaining the ability to identify characteristics and interactions between them.

The first regression tree algorithm publication to appear in literature was proposed by Morgan & Sonquist in 1963 with their research entitled “problems in the analysis of survey data, and a proposal” [Morgan-63]. This algorithm seems appropriate to survey the numerous developments in the different fields of science. The classification regression trees approach is a heuristic trees method that unpacks the relationships between an outcome measure and a group of predictors. The terminology of classification regression tree, each box will represent a group or sub-group called node, the node on the top of a tree is called the root node because the analysis descends from this node. The classifications regression tree analysis is full of partitions at different branches or at different levels. Partition refers to the splitting of cases in a node into groups. When a partition is made in classification regression tree, one node produces two consequent nodes. The produced nodes are called child nodes, whereas the producing node is called the parent node. The node than cannot be further partitioned into child nodes marks the end of growth in that part of the tree and is called a terminal node [Ma-18].

For classification regression trees, the partitioning of cases into groups at each level is guided not by any statistical test but by a statistical criterion referred to as impurity [Breiman-84]. Impurity measures the degree to which cases in a group belong to different categories (values) of the dependent variable. Although impurity can be conceptually defined in different ways, all measures of impurity share the same behavior. The impurity of a node is zero if all cases in that node belong to a single category of the dependent variable, and impurity becomes large if an equal number of cases belong to different categories of the dependent variable. One popular impurity measure is the entropy impurity given by Eq. (2-6).

$$i(\tau) = -\sum P(c_j) \log P(c_j) \tag{2-6}$$

where $P(c_j)$ represents the probability that a case falls into the category c_j or the proportion of the cases that go into that category in node τ. Logarithm is base 2.

A closely related issue to the above discussion is when one should stop partitioning [Ma-18]. A stopping rule is used to stop the partitioning process. Caution is needed when setting the stopping rule. If the rule stops the partitioning too soon, the resulting tree is likely to be too small to reflect the structure of the data. In other words, the error in the structure of the tree tends to be large, which compromises the function of the tree. If the rule stops the partitioning too late, the resulting tree likely to be too large to be either stable or meaningful. In other words, the tree becomes practically useless even though the error in the structure of the tree tends to be small.

There are several different ways to set the stopping rule. Traditionally, one adopts the notion of hypothesis testing to decide when to stop the tree [Duda-01].

In classification problem, we have a training sample of n observations on a class variable Y that takes values $1,2,\dots,k$ and p predictor variables $X_1,\dots,X_p$. Our goal is to find a model for predicting the values of Y from new X values. In theory, the solution is simply a partition of the X space into k disjoint sets, $A_1, A_2, \dots, A_k$, such that the predicted value of Y is j if X belongs to A_j for $j = 1,2,\dots,k$ [Loh-11]. The steps followed for classification trees construction are:

a. Start at the root node.
b. For each X, find the set S that minimizes the sum of the ode impurities in the two child nodes and choose the split $\{X^{*} \epsilon\ S^{*}\}$ that gives the minimum overall X and S.
c. If a stopping criterion is reached, exit. Otherwise, apply step 2 to each child node in turn.

Although regression trees can be generated using many available software, in the present work the regression trees are obtained using Matlab[1] and using holdout validation technique which one is recommended for large data set. For train the model was used 80% of collected data and 20% held out to validate model.

[1] MATLAB, Version 9.8.0, The MathWorks, Inc., 3 Apple Hill Drive, Natick MA 01760-2098, 2019.

2.2.4 Full Factorial Design

It is widely accepted that the most used experimental designs in manufacturing companies are full and fractional factorial designs at two and three levels. Factorial designs would enable an experimenter to study the joint effect of factors (or process/design parameters) on response [Antony-14]. A full factorial designed experiment consists of all possible combinations of levels for all factors. The total number of experiments for studying k factors at 2-levels is 2^k. In order to find the optimal operating conditions by using the trained regression tree model, in this study a full factorial design 2^9 is developed.

The regression tree model previously trained is used to calculate the air output pressure (response variable) for each experiment. The results will be analyzed considering a significance value of 5%. The stepwise method is used to remove the input variables with an alpha value of 0.15 when enter and remove.

2.3. Results and Discussions

After debugging the collected data, the aim of this paper was to fit a multiple linear regression model by considering all the variables shown in Table 2.1. The data was processing by using Minitab software. The results in Table 2.2 shown that the constant term and only eight variables were statistically significant. The pressure of the 50 51 (Press Sec 50 51) dryers were not significant. The resulting regression equation is presented in Eq. (2-7).

$$y = -150.60 - 373.30\,x_1 + 573.00\,x_2 + 968.80\,x_3 - 605.50\,x_5 - 61.40\,x_6 + 26.05\,x_7 + 9.22\,x_8 + 1.80\,x_9 \tag{2-7}$$

For model shown in (2-7), the results shown a determination coefficient of 0.8529 (85.29%) and a standard deviation (s) of 44.6 Pa. In Fig. 2.3 is shown that normality, constant variance, and independence of the residuals are fulfilled.

The results in Table 2.2 shown two variables with the highest VIF values, indicating a serious collinearity problem. Thus, the Reg Pres 50B and Reg Pres 50 were removed from the model. In addition, due to the Steam Press 4 bar do not impact directly in the rodsizer and spooner section, then this variable was also removed. After removing these independent variables, in the following analysis, the Reg Pres Sec 52 54 56 and Pres Sec 52 54 56 variables showed the higher

TABLE 2.2. INITIAL COEFFICIENTS AND P-VALUES

Term	Coef	EE of Coef.	T-value	p-value	VIF
Constant	-1505.6	43.0	-35.05	0.00	
Reg Pres Sec 50B	-373.3	14.9	-25.05	0.00	167.70
Reg Pres Sec 50	573.0	15.5	36.94	0.00	173.31
Reg Pres Sec 52 54 56	968.8	12.3	78.46	0.00	5.66
Pres Sec 52 54 56	-605.5	17.9	-33.83	0.00	12.23
Pres Sec 53 55 57	-61.4	13.1	-4.71	0.00	6.94
Pres Steam 4 bar	26.05	7.63	3.41	0.00	3.70
Pres Steam 10 bar	9.222	0.628	14.68	0.00	1.13
Int Pres (Pa)	1.80621	0.00494	365.68	0.00	1.63

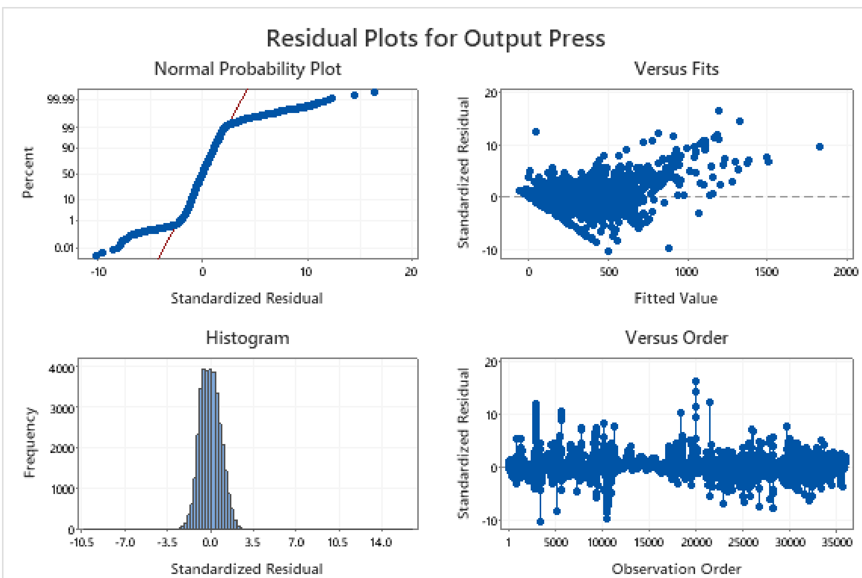


Fig. 2.3 Assumptions of the model.

VIF, however since the Reg Pres Sec 52 54 56 is easier to control in process than Pres Sec 52 54 56 variable, then this was removed. The resulting independent variables are shown in Table 2.3, and the better model is shown in Eq. (2-8).

$$y = -2456.40 + 253.03x_3 - 180.64x_6 + 10.41x_8 + 1.65x_9 \quad (2\text{-}8)$$

With this model, the results shown a determination coefficient of 0.8302, indicating that the model explains 83.02% of the total variability in air output pressure. In addition, the predicted

TABLE 2.3. FINAL COEFFICIENTS AND P-VALUES

Term	Coef	SE of Coef.	T-value	p-value	VIF
Constant	-2456.4	30.0	-81.98	0.00	
Reg Pres Sec 52 54 56	253.03	6.08	41.60	0.00	1.19
Pres Sec 53 55 57	-180.64	5.63	-32.09	0.00	1.12
Pres Steam 10 bar	10.411	0.667	15.62	0.00	1.10
Int Pres (Pa)	1.65272	0.00451	366.49	0.00	1.18

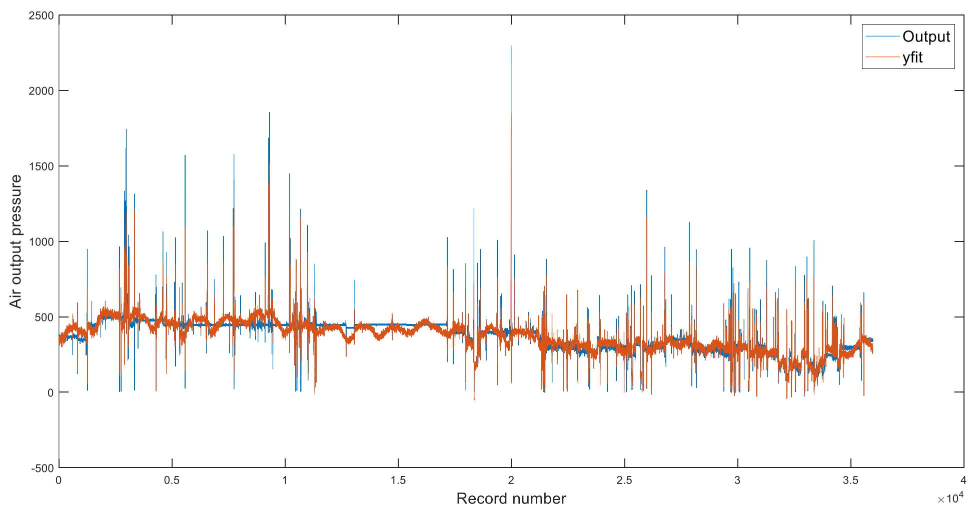


Fig. 2.4 Observed output pressure vs linear regression model.

standard deviation is 47.97 Pa. Although these results are a bit more adverse than the results shown by model in (2-7), with this model the collinearity problem was eliminated.

By using the model shown in Eq. (2-8), a comparison between the observed and predicted values is presented in Fig. 2.4. This model can predict the air output pressure with good precision. and then the model can be used to find the optimal values to keep the process in control (rodsizer-spooner section).

To calculate the composite desirability index (*D*), the response optimizer tool of Minitab[2] was used. In Fig. 2.5 is shown a *D-index* value of 1.000, and the optimal conditions are the next. A differential pressure in dryer 52 54 56 (Reg Pres Sec 52 54 56) of 0.44 bar, a pressure in dryer

[2] Minitab Statistical Software, Version 19.1, Minitab, Inc., State College PA 16801-3210, US, 2019.

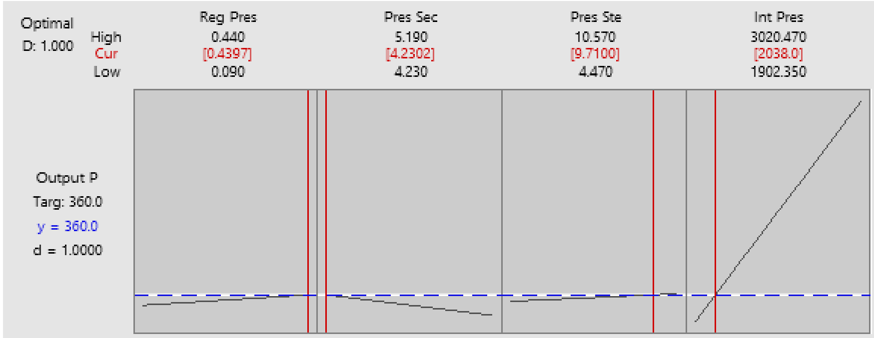


Fig. 2.5 Composite desirability and the optimal setting condition.

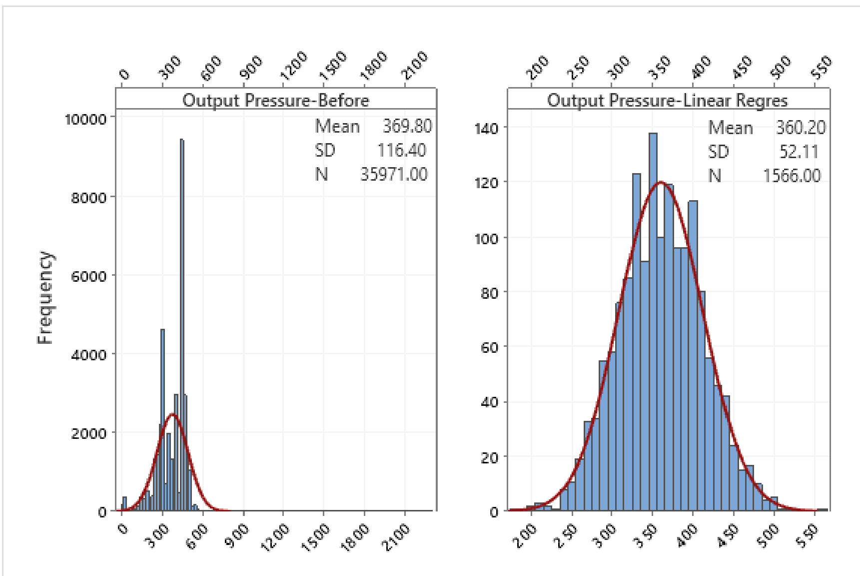


Fig. 2.6 Observed output pressure before and after setting the parameters found by linear regression.

53 55 57 (Pres Sec 53 55 57) of 4.23 bar, a steam pressure in line 10 (Pres Steam 10 bar) of 9.71 bar, and an internal pressure in air box (Int pres) of 2038 Pa. With these operating parameters with a 95% confidence level, the air output pressure was 359.99 Pa. The expected variation is from 350.80 to 369.18 Pa. After the optimal values were setting in the process, the variability in the air output pressure decreased markedly. In Fig. 2.6 is shown a comparison between the process before and after the setting the optimal values.

As alternative, by using machine-learning app in Matlab with the same collected data (35,971), a regression tree model was obtained. The determination coefficient R^2 and root square mean error (RMSE) were the used criteria for selecting the best model. The results shown an R^2 of 92% and RMSE of 32.50. The regression tree model has a very good ability to predict the air

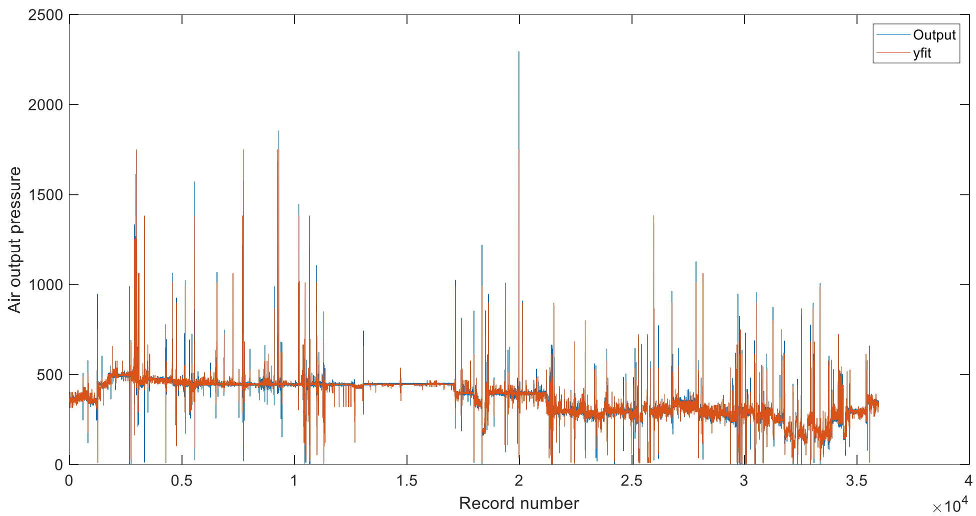


Fig. 2.7 Observed output pressure vs medium tree model.

output pressure as shown in Fig. 2.7.

Since the regression tree model previously trained has good ability to predict the air output pressure, then it is used to evaluate the response in the designed experiment. The approach used is a full factorial 2^9 design. All independent variables were coded and its levels (low and high) defined as shown in the Table 2.4. The variables levels were defined both: based on the process engineers experience and optimal parameters found by linear regression model previously analyzed.

In order to develop the designed experiment, first, a matrix of $512x9$ size was generated in Minitab. The response for each experiment was calculated by using the $yfit = c.predictFcn(X)$ function in Matlab.

After run the experimental design in Minitab, the results show an acceptable standard deviation (s) of 7.87; while, the variability explained by the model is also acceptable with an adjusted determination coefficient (R^2_{adj}) of 96.91%. Before evaluate the individuals' effects and interactions from the analysis of variance, the assumptions of the model must be verified. Fig. 2.8 presents the assumptions of normality, constant variance, and independence. Although constant variance and independence do not show any problem, the normality assumption is clearly not met. This problem is common when data is generated from a regression tree model because it classifies the data into possible categories. Therefore, the conclusions could be wrong. However, since the variables included in this analysis only correspond to those previously found by the linear

TABLE 2.4. CODE AND LEVELS FOR EACH INPUT VARIABLE

Variable name	Code	Levels	
		Low (-)	High (+)
Differential pressure in dryer 50B	A	3.50	4.50
Differential pressure in dryer 50	B	3.50	4.50
Differential pressure in dryer 52 54 56	C	0.35	0.45
Pressure in dryer 50 51	D	3.50	4.50
Pressure in dryer 52 54 56	E	4.00	4.50
Pressure in dryer 53 55 57	F	4.00	4.50
Steam pressure Line 4	G	4.00	5.00
Steam pressure Line 10	H	9.00	9.50
Internal pressure of air box	J	2000.00	2050.00

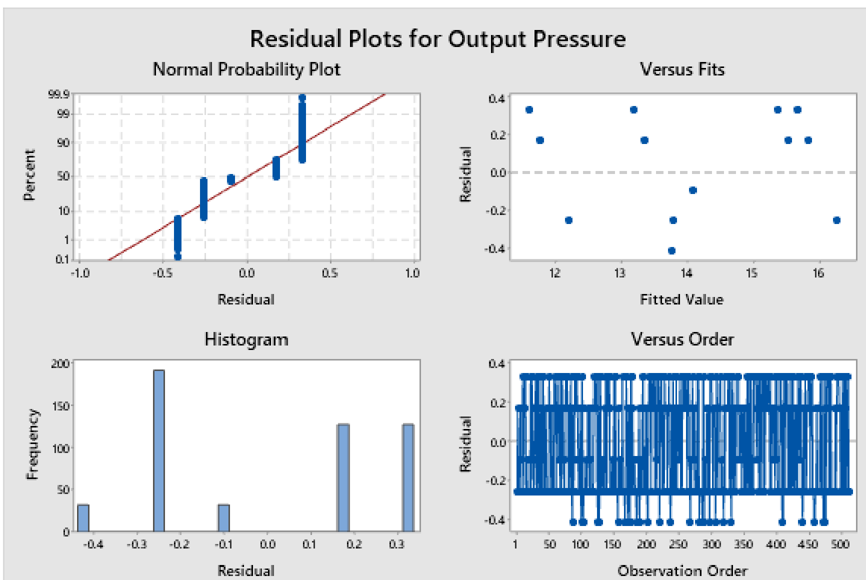


Fig. 2.8 Assumptions of the model with data generated using the regression tree model.

regression model, the present analysis is intended to find and validate the operating conditions.

Therefore, since the objective is defining the optimal operating conditions that let the output pressure gain stability. From the ANOVA presented in Table 2.5, the main effects and interactions are analyzed. From this table, the individual effects as differential pressure in dryer 52 54 56 (C), pressure in dryer 50 51 (D), steam pressure line 10 (H), and internal pressure of the air

TABLE 2.5. ANALYSIS OF VARIANCE

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	994893	110544	1781.61	0.000
Linear	4	935765	233941	3770.39	0.000
C	1	206972	206972	3335.74	0.000
D	1	28620	28620	461.27	0.000
H	1	629	629	10.14	0.002
J	1	699543	699543	11274.41	0.000
2-Way Interactions	5	59128	11826	190.59	0.000
C*D	1	28620	28620	461.27	0.000
C*H	1	629	629	10.14	0.002
D*H	1	629	629	10.14	0.002
D*J	1	28620	28620	461.27	0.000
H*J	1	629	629	10.14	0.002
Error	502	31148	62		
Total	511	1026041			

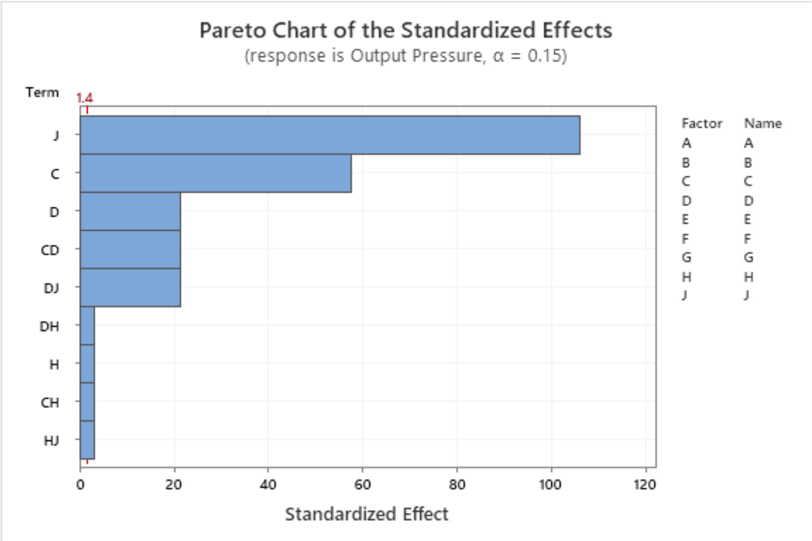


Fig. 2.9 Pareto chart of the magnitude and importance of individual effects and interactions.

box (J) were significant at 5%. Meanwhile, the two-way interactions as differential pressure in dryer 52 54 56 (C)*pressure in dryer 50 51 (D), differential pressure in dryer 52 54 56 (C)*steam

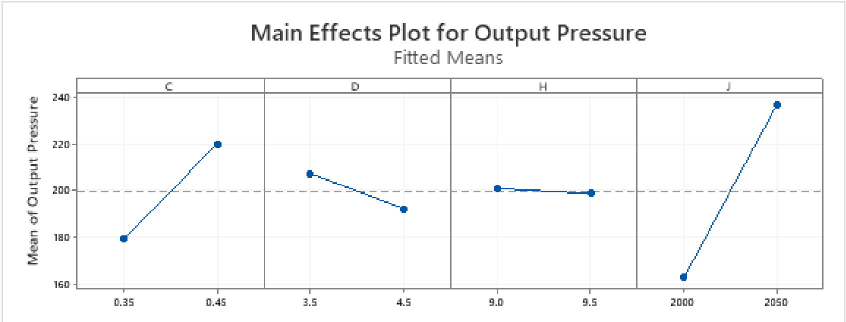


Fig. 2.10 Main effects plot for response.

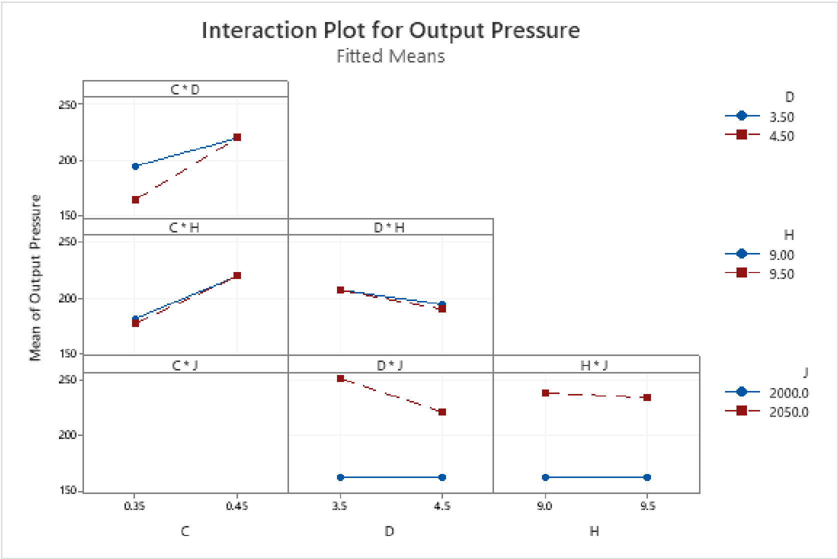


Fig. 2.11 Interaction plot for response.

pressure line 10 (H), pressure in dryer 50 51 (D)*steam pressure line 10 (H), pressure in dryer 50 51 (D)*internal pressure of the air box (J), and steam pressure line 10 (H)*internal pressure of the air box (J) were significant at 5%. In Fig. 2.9 is shown the magnitude and importance of the individual effects and interactions.

The optimal operating parameters are obtained from the main effects and interactions plots as shown in the Fig. 2.10 and Fig. 2.11 respectively. Since the interactions were significant, the optimal operating conditions are obtained from the interaction plot. Thus, from Fig. 2.11, the optimal operating conditions are: 0.45, 3.50, 9.00 and 2050.00 to differential pressure in dryer 52 54 56 (C), pressure in dryer 50 51 (D), steam pressure line 10 (H) and the internal pressure of the air box (J) respectively. The rest of the input variables were removed because they had no effect on the air output pressure.

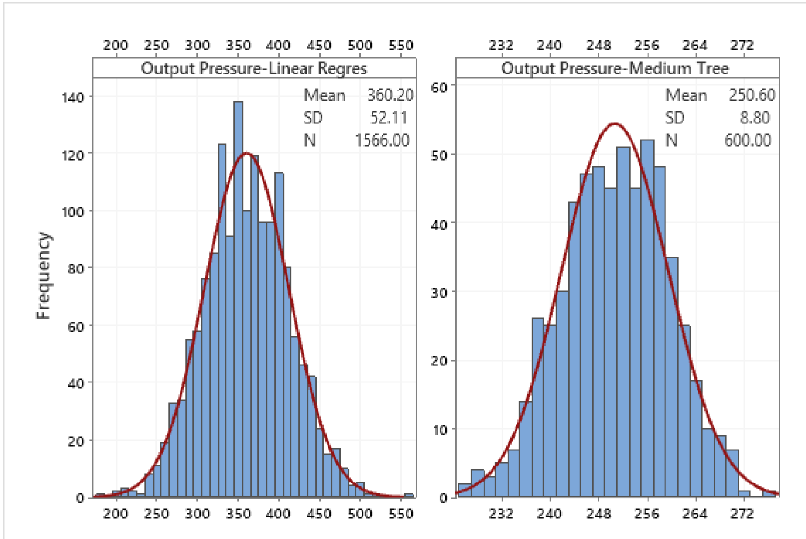


Fig. 2.12 Observed output pressure before and after setting the parameters found by regression tree model.

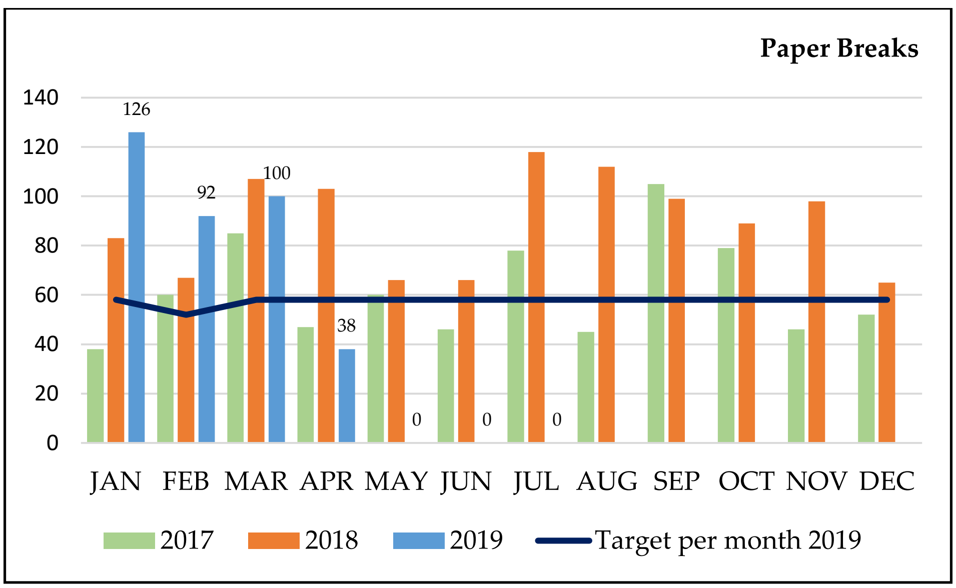


Fig. 2.13 Paper tear offs reported before and after parameters optimization.

A lower air output pressure indicates that the paper web will be closer to the air box (air tum shown in Fig. 2.2). The optimal operating conditions found by using the regression tree model and designed experiment approach were tested over 10 hours. In addition, in Fig. 2.12 is shown a comparison between linear regression and regression tree model developed. The results show that regression tree model has the lowest values in the mean and standard deviation, demonstrating a clear advantage over the linear regression model. Finally, by using the records used in process, a time-based bar plot for the paper tear offs per month is presented in Fig. 2.13. The results shown that no paper tear offs were observed over a three months' period, while the output pressure was below 100 Pa.

Although, the optimal operating conditions found by the two methods are very similar, by using the regression tree model, the process was able to work with a lower pressure in line 10, generating a saving of 0.71 bar.

2.4. Conclusions

The instability in the air output pressure of the air box through which the paper passes in the rodsizer of a paper machine is the main cause of most paper breaks problems in this section, and consequently of downtime. This specific papermaking section has not been exploited by using regression techniques.

Taking advantage of data available, as a first step, a linear regression model was trained and developed. This research demonstrated that fitted models has an acceptable predictive capacity, and the operating parameters estimated allowed to reduce variability in the air output pressure, and therefore, to minimize the paper tear offs. Although, the collinearity problem was not the purpose of this work, the mechanical solution of this problem is an excellent alternative when the process is widely known. After three months, the optimal operating conditions found by the regression model are acceptable. While the air output pressure was below 100 Pa no stoppages due to variability problems was reported as shown in Fig. 2.13.

As alternative, with the same collected data and a regression model was trained by using machine learning app in Matlab. Based on R^2 and RMSE, the medium regression tree was the best model. The results show that regression tree model has a better predictive capacity than linear regression model.

In order to find optimal operating conditions, by using the regression tree model as source of output pressure measurement, a full factorial design was developed. Findings show that linear regression and regression tree models found only four independent variables as significant. It was possible to obtain a significant reduction in the consumption of the steam pressure in line 10, from 9.71 bar defined by the linear regression model to 9.00 bar defined by the regression tree model. The regression tree model demonstrated a clear advantage over the linear regression model because better operating conditions and less variability in output pressure were found.

Since non-invasive experiments reduce the risk of low quality and downtime, besides by considering the described assumptions above, one of the most significant findings from this study is that the proposed approach: modeling in addition to designed experiments could be implemented to other complex process sections. Further research should be carried out to compare the results found here against the results by using neural network models.

3. Analysis and Control of the Paper Moisture Content Variability by Using Fuzzy and Traditional Individual Control Charts

For several decades, the fuzzy theory has been used to develop the so-called fuzzy control charts to analyze process data in a more reliable and flexible way than traditional control charts. Control charts are more commonly used in the papermaking processes to check the stability of the data source. These charts are conceived as devices that enhance routine time-by-time adjustments during the production process, so their value is incomparable. A critical variable that must be controlled during the papermaking process is the moisture content of the paper. However, due to the paper's hygroscopic characteristics, its moisture content values may carry some uncertainty derived from measurement systems and the nature of the papermaking process. Therefore, an alternative approach that includes fuzzy control charts to handle these uncertainties is proposed in this paper. The method to convert individual data to fuzzy numbers is based on the sigma level process as a first stage, and then, the fuzzy individual and moving range control charts are introduced using the α-cut fuzzy midrange approach. Data from the moisture content of a 240 grams/m^2 coated paper sample is used to prove the performance of the fuzzy individual control charts. According to the proposed methodology, findings show that fuzzy individual and moving range control charts have greater flexibility by reflecting a larger amplitude of their control limits, in addition to a lower number of "out of control" values.

3.1. Introduction

A standard papermaking machine production line includes the following sections: stock preparation, wire (or forming), wet pressing, drying, coating, calendaring, and rolling of paper on a reel. A standard scheme of a papermaking production line is shown in Fig. 3.1. The stock preparation process converts the raw stock into finished stock through several steps, such as fiber disintegration, cleaning, and chemical mixing. The pulp formed is refined and after it has been cleaned and diluted, the pulp stock is transferred into the white-water system, which is the headbox

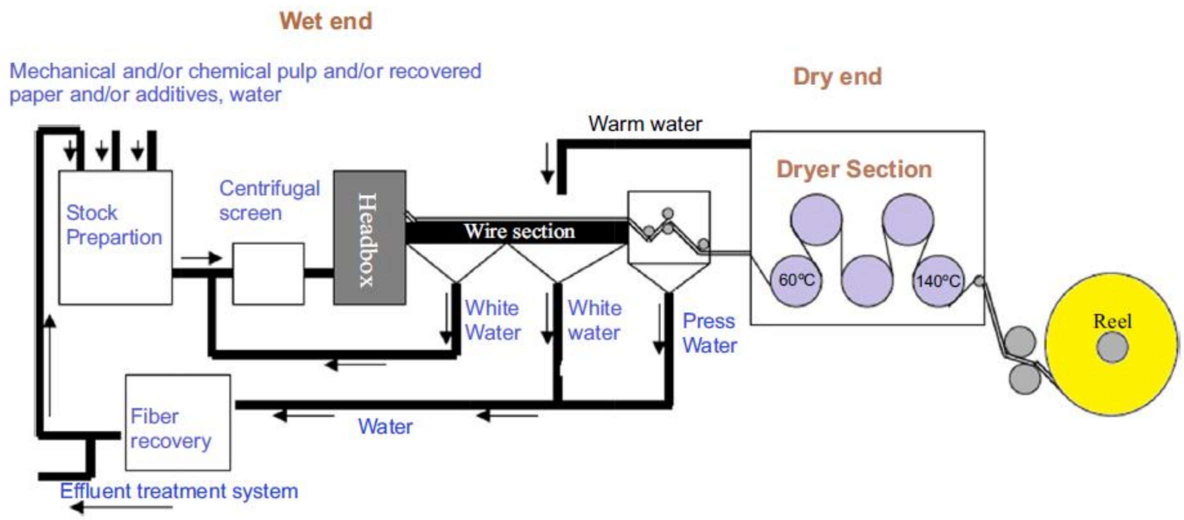


Fig. 3.1 The standard scheme of the papermaking line (taken from [Bajpai-15]).

and mesh of wires where water circulates and is filtered. The white water dilutes the stock to its desired consistency for the paper web forming process, and the headbox spreads the stock on the wire mesh across the width of the paper machine that forms the paper web. The vacuum boxes located under the wire, aid in the water draining operation in a short distance. Afterward, the web enters the press section where it undergoes compression between two rotating rolls to squeeze out more water. The paper web continues the process in the drying section where the web is passed through the rotating steam-heated dryer rollers removing moisture by evaporation. When the paper grade requires a coating process, then the web continues to a second drying operation before entering the calendaring stack. The finished product from the papermaking machine is wound onto a reel to the desired roll diameter before being dispatched to the customer [Bhutani-15].

The papermaking process has multiple variables that affect product quality, as basis weight, thickness (caliper), moisture content, ash content, and fiber orientation [Merbold-16]; in addition, whiteness is an important property of white paper [Tarasov-18]. Thus, it is important to monitor these variables. Commonly, the basis weight, caliper, and moisture content are automatically monitored through a scanner [Raunio-18], and the remaining variables by using manually developed control charts. Currently, after the rolling step, the paper moisture content monitoring process of these variables would not be appropriate, because throughout the paper supply chain, environmental storage conditions are highly variable, thus, these factors will affect the paper moisture content. For instance, Karthik et al. [Karthik-12] found that large variations on relative humidity will affect the paper moisture content creating a paper curl, which adversely affects postprocessing units like calendaring, including the converting or packaging line, or even the customer´s printing press (worsening printability). For this reason, some studies have highlighted the need to have a robust monitoring technique capable of identifying small shifts and common sources of variation and process stability [Hadian-19; Keller-19; Rukhsar-19].

Monitoring the quality of product characteristics, either of a variable or attribute type, plays a key role in a successful quality improvement to reduce process or product variation [Kim-19]. For this purpose, the traditional control chart technique has been used in a variety of manufacturing and service industries where the control charts are based on the sample mean ($\bar{X}$), range (R), standard deviation (s), individual data (X), and moving range (MR) [Mitra-19]. For the moving range (MR), the subgroup size is 1 and the process is monitored based on individual observations [Mitra-16]. In all other cases, the subgroup size is greater than one, samples are randomly selected, and data independence is assumed. Other types of control charts are the exponentially weighted moving average (EWMA) and cumulative sum (CUSUM) charts, which are less used but very effective in detecting small shifts [Haq-19]. In a series of EWMA charts, data tends to move slowly to the new level after a shift in the process, or it will vary around the centerline when small fluctuations are present [Şentürk-14]. Meanwhile, the CUSUM chart represents the cumulative sum of the process deviations, containing information from previous samples [Boullosa-Falces-19]; nevertheless, these charts are only effective for known shift sizes or when the control chart is designed for a specific shift size.

Nonetheless, one of the main objectives of any control chart approach is to determine whether the process is under or out of control. As a part of the procedure to elaborate a control chart, data collection is required to prepare preliminary information and thus, establish the central line and the two control lines (or one line, when only the deviation of a process level in one direction is of interest). Typically, the process is declared under control (stable) when the data collected are located within the two control lines following a random cyclic pattern, although other patterns also carry a similar statement [Montgomery-07]. When an observation falls outside of the control lines or certain run criteria are shown by the data, an alarm signal is generated, and the process is considered potentially out of control (unstable) [Hryniewicz-19].

The approach used to determine stability in the papermaking process is commonly through traditional control charts, at least for base weight, caliper, or paper moisture content. In addition, since the cycle time in the papermaking process usually takes at least 30 minutes (depending on the machine's speed), then individual measurement control charts are the most appropriate [Oakland-07]. As mentioned above, traditional control charts have been used in different industries [Kim-19; Haq-19; Camargo-10; Dudek-Burlikowska-05; Shamsuzzaman-15; Zaman-20; Zhiyuan-15] but in all cases, the traditional approach assumes that the process data follows a normal distribution. Traditional control charts are suitable for well-known and precise data cases, but for the papermaking process, the data usually shows some of these uncertain elements, mainly in the paper moisture content. The fuzzy theory has been widely used to solve uncertainty problem of the data [Sun-18]. The fuzzy set theory, proposed by Zadeh [Zadeh-65] is used for modeling the data uncertainties of natural language processing and it can be applied in many areas, such as optimization, automatic control systems, information systems, imaging systems, and decision making.

For at least three decades, trends in research have dealt with the issue of control charts based on the fuzzy set theory [Chang-96; Cheng-05; Gülbay-06; Gülbay-07; Kaya-11a; Shu-11], and currently, this approach is still widely used [Hryniewicz-19; Hesamian-18; Kaya-17; Shabani-18; Bazhanov-20; Kaya-20; Choi-20; Ercan-Teksen-20]. The fuzzy approach has been introduced in different processes. For instance, in a plastic process, Şentürk et al. [Şentürk-14] proposed a fuzzy EWMA control chart for univariate data, in healthcare, Chang et al. [Chang-16] used a multilevel chart and fuzzy set theory to monitor inpatient falls, and in furniture manufacturing Sagnak and Kazancoglu [Sagnak-20] proposed a fuzzy analytic hierarchy process-integrated statistical process control. However, the fuzzy set theory has been poorly studied for the papermaking process.

The company investigated in this study has three production lines: paper, corrugated cardboard boxes, and high graphic boxes. Among its quality control strategies, the company uses traditional control charts, mainly between the end of the papermaking process and at the beginning of the corrugated process. However, due to the characteristics of the paper materials, the paper moisture content is affected in high-humidity environments, thus, it is essential to understand how the moisture content of the product varies under different storage and distribution environments [Parker-06], in addition to measuring uncertainty, which has been accepted as a property of the measurement itself [Clippinger-12]. These two factors could cause measurements to exceed the control limits, and therefore, wrongly conclude the stability process when the variation in paper moisture content is minimal. This is a common topic of discussion between the paper supplier and its customer. Thus, developing a fuzzy control chart with more flexibility to monitor the paper moisture content is necessary.

In the present chapter it is proposed the fuzzy control charts for individual measurements in the papermaking process by using the fuzzy individual control charts (FICC) and fuzzy moving range control charts (FMRCC) proposed by Kaya et al. [Kaya-17]. However, unlike the Kaya et al. approach, the proposed method, generates the fuzzy numbers based on the observed variation for the selected time and the sigma level of the process. This methodology has not been studied nor employed in the papermaking process to control the paper moisture content. This chapter is organized as follows: Section 2 presents a brief review of fuzzy control charts for individual measurements and transformation techniques, in addition details the proposed methodology to build a fuzzy individual control chart. Section 3 presents a real case application in the papermaking process. Finally, the last two sections include the results and conclusions.

3.2. Methodology

It is possible to create from fuzzy control charts by translating linguistic variables to fuzzy numbers or by using them directly without any transformation. A fuzzy number is a generalization of a regular real number in a way that it does not refer to one single value but rather to a connected set of possible values. A formal concept of a fuzzy set $\tilde{A}$ on real number system R needs to satisfy the following properties: 1) $\tilde{A}$ is normal i.e., $\exists x_0 \in R$ such that $\mu_{\tilde{A}}(x_0) = 1$; 2) $\tilde{A}_\alpha$ is a closed interval for every $\alpha \in (0, 1]$; and 3) the support $S(\tilde{A})$ is bounded [Klir-95]. Fuzzy numbers can be classified into various categories depending on their respective membership functions, such as: Triangular Fuzzy Number (TFN), Trapezoidal Fuzzy Number (TrFN), and Gaussian Fuzzy Number (GFN) [Chakraverty-19]. Considering that most measurements in the papermaking process tend to be at the center of the specification, at least for basis weight, caliper, and moisture content, thus, the triangular fuzzy number is used in this work. A fuzzy number A is called a triangular fuzzy number if its membership function $A(x)$ has the (3-1) form [Zeng-07].

(3-1)

$$A(x) = \begin{cases} 0, & x \leq b - a \\ \dfrac{x - b + \alpha}{\alpha}, & b - a < x < b \\ 1, & x = b \\ \dfrac{b + \beta - x}{\beta} & b < x < b + \beta \\ 0, & b + \beta < x \end{cases}$$

where parameters α and β are positive real numbers, and are called left and right width, respectively. By using the notation in [Dubois-78], the fuzzy number can be written as: $A = (b, \alpha, \beta)$. Therefore, in the case study these parameters correspond to the sample measurement and the extreme values. So, control limits in a fuzzy control chart are named fuzzy control limits, which can be calculated by using fuzzy numbers in classical control charts for individual measurements [Kaya-17]. According to the TFN, (X_a, X_b, X_c) used for the selected sample, the fuzzy sample mean $(\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c)$, which constitutes the centerline of the control chart, $(\widetilde{CL})$ is calculated as shown in (3-2) and (3-3).

$$\bar{X}_{k_j} = \frac{\sum_{i=1}^{n} X_{k_{ji}}}{n}; k = a, b, c; i = 1,2, \dots, n; j = 1,2, \dots, m \tag{3-2}$$

$$\widetilde{CL} = \left(\frac{\sum_{j=1}^{m} X_{a_j}}{m}, \frac{\sum_{j=1}^{m} X_{b_j}}{m}, \frac{\sum_{j=1}^{m} X_{c_j}}{m}\right) = \left(\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c\right) \tag{3-3}$$

where n is the sample size, m is the number of samples and $(\widetilde{CL})$ is the center line for FCCIM. The fuzzy moving range $(\widetilde{MR})$ for FCCIM can be calculated as seen from (3-4) to (3-7).

$$\tilde{X}_i = \left(\bar{X}_{a_i}, \bar{X}_{b_i}, \bar{X}_{c_i}\right) \tag{3-4}$$

$$\widetilde{MR} = (\overline{MR}_a, \overline{MR}_b, \overline{MR}_c) \tag{3-5}$$

$$\widetilde{MR}_i = \left|\left(\bar{X}_{a_i}, \bar{X}_{b_i}, \bar{X}_{c_i}\right) - \left(\bar{X}_{a_{i-1}}, \bar{X}_{b_{i-1}}, \bar{X}_{c_{i-1}}\right)\right| \tag{3-6}$$

$$\widetilde{MR} = \left|\frac{\sum_{j=1}^{m} MR_{a_j}}{m-1}, \frac{\sum_{j=1}^{m} MR_{b_j}}{m-1}, \frac{\sum_{j=1}^{m} MR_{c_j}}{m-1}\right| \tag{3-7}$$

The proposed method to generate the fuzzy numbers was based on the observed variation for the selected sample and the sigma level of the process. Therefore, the fuzzy numbers were calculated by using from (3-8) to (3-10).

$$X_{a_j} = X_j - 2s_j \tag{3-8}$$

$$X_{b_j} = X_j \tag{3-9}$$

$$X_{c_j} = X_j + 2s_j \tag{3-10}$$

where s is the standard deviation in the sample j, X_j is the moisture measure in sample j, two number is the sigma level accepted for the process (the accepted sigma level for the papermaking process is two; however, this value may be different according to the industrial process) and $\left(X_{a_j}, X_{b_j}, X_{c_j}\right)$ is the fuzzy number of sample j.

When the fuzzy numbers have been generated, then, the center ($\widetilde{CL}$), upper ($U\tilde{C}L$), and lower ($L\tilde{C}L$) fuzzy control limits for the fuzzy individual control chart (FICC) and fuzzy moving range control chart (FMRCC) were calculated according to the method proposed by Kaya et al. [Kaya-17].

The fuzzy control limits for the fuzzy individual control chart were calculated as shown from (3-11) to (3-13).

$$U\tilde{C}L_{\bar{X}} = \left(\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c\right) + 3\,\frac{(\overline{MR}_a, \overline{MR}_b, \overline{MR}_c)}{d_2} \tag{3-11}$$

$$\widetilde{CL}_{\bar{X}} = \left(\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c\right) \tag{3-12}$$

$$L\tilde{C}L_{\bar{X}} = \left(\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c\right) - 3\,\frac{(\overline{MR}_a, \overline{MR}_b, \overline{MR}_c)}{d_2} \tag{3-13}$$

where d_2 is a used factor with the control charts for continuous data. While, the fuzzy control limits for fuzzy moving range control chart were calculated as shown from (3-14) to (3-16).

$$U\tilde{C}L_{\overline{MR}} = d_4(\overline{MR}_a, \overline{MR}_b, \overline{MR}_c) \tag{3-14}$$

$$\widetilde{CL}_{\overline{MR}} = (\overline{MR}_a, \overline{MR}_b, \overline{MR}_c) \tag{3-15}$$

$$L\tilde{C}L_{\overline{MR}} = d_3(\overline{MR}_a, \overline{MR}_b, \overline{MR}_c) \tag{3-16}$$

where d_4 and d_3 are factors to be used with the control charts.

Since it is possible to develop charts of fuzzy control charts by converting linguistic variables to fuzzy numbers, the present paper uses this approach to develop the proposed fuzzy control charts. In order to do the conversion of the linguistic variables, some fuzzy transformations techniques can be found in the literature, such as fuzzy mode, α-cut fuzzy midrange, fuzzy median, fuzzy average, and direct fuzzy approach [Kaya-17; Wang-90]. In this work, the transformation technique used to calculate the new fuzzy control limits is the α-cut fuzzy midrange proposed by Kaufmann and Gupta [Kaufmann-85].

The α-cut fuzzy midrange f_{mr}^{α} is defined as the midpoint of the ends of the α-level cuts. An α-level cut, denoted by A^{α}, is a non-fuzzy set that comprises all elements whose membership is greater than or equal to α. If a^{α} and b^{α} are the end points of A^{α}, then f_{mr}^{α} is calculated as shown in (3-17) [Senturk-09].

$$f_{mr}^{\alpha} = \frac{1}{2}(a^{\alpha} + b^{\alpha}) \tag{3-17}$$

In fact, the fuzzy mode is a special case of α-cut fuzzy midrange when $\alpha = 1$. α-cut fuzzy midrange of sample j, $S_{mr,j}^{\alpha}$, is determined by (3-18).

$$S_{mr,j}^{\alpha} = \frac{(a_j+c_j)+\alpha[(b_j-a_j)-(c_j-b_j)]}{2} \tag{3-18}$$

The α-cut fuzzy midrange control limits for the α-cut fuzzy control charts is calculated as shown from (3-19) to (3-21).

$$CL_{mr}^{\alpha} = f_{mr}^{\alpha}\left(\widetilde{CL}\right) \tag{3-19}$$

$$LCL_{mr}^{\alpha} = CL_{mr}^{\alpha} - 3\sqrt{CL_{mr}^{\alpha}} \tag{3-20}$$

$$UCL_{mr}^{\alpha} = CL_{mr}^{\alpha} + 3\sqrt{CL_{mr}^{\alpha}} \tag{3-21}$$

In order to define the process situation (whether the process is in control or not), (3-22) can be used.

$$Process\ Situation = \begin{cases} in\ control, if\ \left(LCL_{mr}^{\alpha} \leq S_{mr,j}^{\alpha} \leq UCL_{mr}^{\alpha}\right) \\ out\ of\ control, otherwise. \end{cases} \tag{3-22}$$

When the α-cut approach has been applied to each sample j where $S_{mr.j}^{\alpha}$ and to the fuzzy control limits, the reformulation of $\bar{\bar{X}}_a^{\alpha}$, $\bar{\bar{X}}_c^{\alpha}$, $\overline{MR}_a^{\alpha}$ and $\overline{MR}_c^{\alpha}$ are shown from (3-23) to (3-28).

$$\bar{\bar{X}}_a^{\alpha} = \bar{\bar{X}}_a + \alpha\left(\bar{\bar{X}}_b - \bar{\bar{X}}_a\right) \tag{3-23}$$

$$\bar{\bar{X}}_b^{\alpha} = \bar{\bar{X}}_b \tag{3-24}$$

$$\bar{\bar{X}}_c^{\alpha} = \bar{\bar{X}}_c - \alpha\left(\bar{\bar{X}}_c - \bar{\bar{X}}_b\right) \tag{3-25}$$

$$\overline{MR}_a^{\alpha} = \overline{MR}_a + \alpha(\overline{MR}_b - \overline{MR}_a) \tag{3-26}$$

$$\overline{MR}_b^{\alpha} = \overline{MR}_b \tag{3-27}$$

$$\overline{MR}_c^{\alpha} = \overline{MR}_c - \alpha(\overline{MR}_c - \overline{MR}_b) \tag{3-28}$$

Therefore, the fuzzy control limits for individual measurements with the α-cuts applied were calculated by using from (3-29) to (3-31).

$$U\tilde{C}L_{\bar{X}}^{\alpha} = \left(\bar{\bar{X}}_a^{\alpha}, \bar{\bar{X}}_b^{\alpha}, \bar{\bar{X}}_c^{\alpha}\right) + 3\,\frac{(\overline{MR}_a^{\alpha}, \overline{MR}_b^{\alpha}, \overline{MR}_c^{\alpha})}{d_2} \tag{3-29}$$

$$\widetilde{CL}_{\bar{X}}^{\alpha} = \left(\bar{\bar{X}}_a^{\alpha}, \bar{\bar{X}}_b^{\alpha}, \bar{\bar{X}}_c^{\alpha}\right) \tag{3-30}$$

$$L\tilde{C}L_{\bar{X}}^{\alpha} = \left(\bar{\bar{X}}_a^{\alpha}, \bar{\bar{X}}_b^{\alpha}, \bar{\bar{X}}_c^{\alpha}\right) - 3\,\frac{(\overline{MR}_a^{\alpha}, \overline{MR}_b^{\alpha}, \overline{MR}_c^{\alpha})}{d_2} \tag{3-31}$$

where d_2 is a factor to use with the control chart. While, the fuzzy control limits for moving ranges with the α-cuts were calculated by using from (3-32) to (3-34).

$$U\tilde{C}L_{MR}^{\alpha} = d_4(\overline{MR}_a^{\alpha}, \overline{MR}_b^{\alpha}, \overline{MR}_c^{\alpha}) \tag{3-32}$$

$$\widetilde{CL}_{MR}^{\alpha} = (\overline{MR}_a^{\alpha}, \overline{MR}_b^{\alpha}, \overline{MR}_c^{\alpha}) \tag{3-33}$$

$$L\tilde{C}L_{MR}^{\alpha} = d_3(\overline{MR}_a^{\alpha}, \overline{MR}_b^{\alpha}, \overline{MR}_c^{\alpha}) \tag{3-34}$$

where d_4 and d_3 are factors to be used with the control charts.

Finally, the α-cut control limits are converted to fuzzy values by using the fuzzy midrange approach. Thus, the control limits for the fuzzy individual control charts were recalculated as shown from (3-35) to (3-37).

$$UCL_{mr-X}^{\alpha} = \left(\frac{\bar{\bar{X}}_a^{\alpha} + \bar{\bar{X}}_c^{\alpha}}{2}\right) + 3 * \frac{\left(\frac{\overline{MR}_a^{\alpha} + \overline{MR}_c^{\alpha}}{2}\right)}{d_2} \tag{3-35}$$

$$CL_{mr-X}^{\alpha} = \left(\frac{\bar{\bar{X}}_a^{\alpha} + \bar{\bar{X}}_c^{\alpha}}{2}\right) \tag{3-36}$$

$$LCL_{mr-X}^{\alpha} = \left(\frac{\bar{\bar{X}}_a^{\alpha} + \bar{\bar{X}}_c^{\alpha}}{2}\right) - 3 * \frac{\left(\frac{\overline{MR}_a^{\alpha} + \overline{MR}_c^{\alpha}}{2}\right)}{d_2} \tag{3-37}$$

In order to calculate the fuzzy midrange values and to determine the process situation for the fuzzy individual control charts, (3-18) and (3-22) were rewritten as shown in (3-38) and (3-39) respectively.

$$S_{mr-X}^{\alpha} = \frac{\left(X_{a_j} + X_{c_j}\right) + \alpha\left[\left(X_{b_j} - X_{a_j}\right) - \left(X_{c_j} - X_{b_j}\right)\right]}{2} \tag{3-38}$$

$$Process\ Situation = \begin{cases} incontrol, \quad if\ \left(LCL_{mr-X}^{\alpha} \leq S_{mr-X_j}^{\alpha} \leq UCL_{mr-X}^{\alpha}\right) \\ \qquad out\ of\ control, otherwise. \end{cases} \tag{3-39}$$

While, the control limits for the fuzzy moving range control charts were recalculated as shown from (3-40) to (3-42).

$$UCL_{mr-MR}^{\alpha} = D_4\left(\frac{\overline{MR}_a^{\alpha} + \overline{MR}_c^{\alpha}}{2}\right) \tag{3-40}$$

$$CL_{mr-MR}^{\alpha} = \left(\frac{\overline{MR}_a^{\alpha} + \overline{MR}_c^{\alpha}}{2}\right) \tag{3-41}$$

$$LCL_{mr-MR}^{\alpha} = D_3\left(\frac{\overline{MR}_a^{\alpha} + \overline{MR}_c^{\alpha}}{2}\right) \tag{3-42}$$

To calculate the fuzzy midrange values and to determine the process situation for the fuzzy moving range control charts, (3-18) and (3-22) were also rewritten as shown in (3-43) and (3-44) respectively.

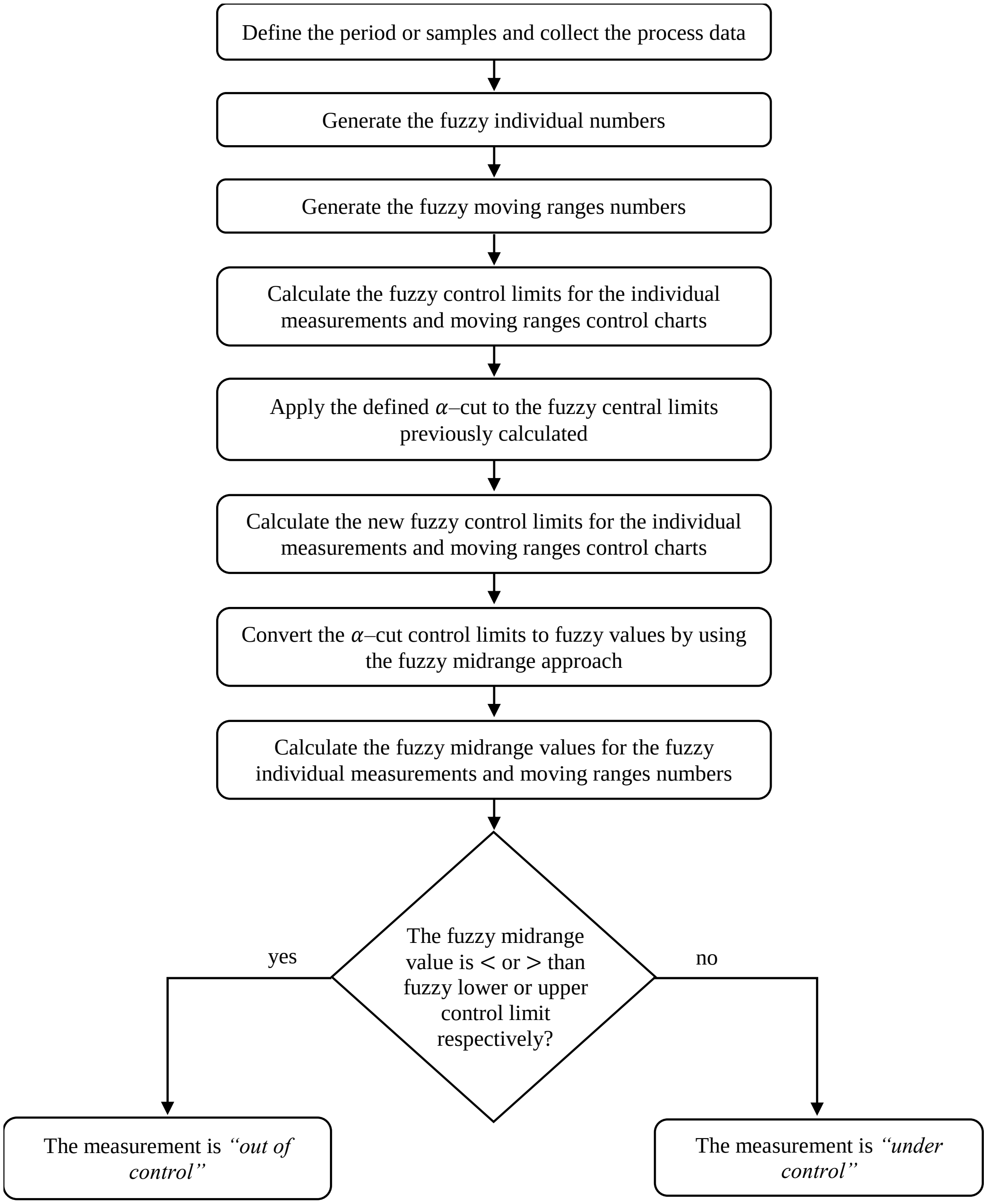


Fig. 3.2 Methodology to develop a flexible fuzzy control chart for individual measurements.

$$S^{\alpha}_{mr-MR} = \frac{\left(MR_{a_j}+MR_{c_j}\right)+\alpha\left[\left(MR_{b_j}-MR_{a_j}\right)-\left(MR_{c_j}-MR_{b_j}\right)\right]}{2} \tag{3-43}$$

$$Process\ Situation = \begin{cases} incontrol, & if\ \left(LCL^{\alpha}_{mr-MR} \leq S^{\alpha}_{mr-MR_j} \leq UCL^{\alpha}_{mr-MR}\right) \\ & out\ of\ control, otherwise. \end{cases} \tag{3-44}$$

An overall scheme of the proposed methodology to develop the flexible fuzzy control chart for individual measurements is shown in Fig. 3.2.

To demonstrate the advantages of the proposed method, the traditional individual control charts were developed by using the same collected process data [Hadian-19]. The control limits for individuals control chart were calculated by using from (3-45) to (3-47).

$$U\tilde{C}L_{\bar{X}} = \bar{X} + 3\,\frac{\bar{R}}{1.128} \tag{3-45}$$

$$\widetilde{CL}_{\bar{X}} = \bar{X} \tag{3-46}$$

$$L\tilde{C}L_{\bar{X}} = \bar{X} - 3\,\frac{\bar{R}}{1.128} \tag{3-47}$$

where $\bar{X}$ is the average of data collected, and $\bar{R}$ is the average range. While, the control limits for moving ranges control chart were calculated by using (3-48) to (3-50).

$$U\tilde{C}L_{MR} = 3.277 * \bar{R} \tag{3-48}$$

$$\widetilde{CL}_{MR} = \bar{R} \tag{3-49}$$

$$L\tilde{C}L_{MR} = 0 \tag{3-50}$$

For the traditional individual control chart, a measurement will be declared as “out of control” if the data is above or below its upper and lower control limits, respectively. While for the traditional moving range control chart, a measurement will be declared as “out of control” if the data is above or below its upper and lower control limits, respectively.

3.3. A Real Case Application

The pulp and paper industry is a large and growing portion of the world’s economy and its production has increased globally and is expected to continue rising in the coming years [Bajpai-12]. The most important variables affecting the product quality in the papermaking process are basis weight, thickness (caliper), and moisture content for kraft and coated paper. Xie and Chai [Xie-16] mention that the moisture content in paper materials and products plays an important role in the process control and optimization of industrial applications. Furthermore, Dimmick [Dimmick-07] shows that moisture content in paper materials can affect many physical paper properties (such as stiffness, smoothness, and tensile strength), which are important for product performance. For Rhim [Rhim-10] it is important to understand what makes the moisture content vary under different relative humidity (RH) and temperature environmental conditions, and how the resulting paper moisture content affects the mechanical properties of packing materials. The quality control systems of brands, such as ABB and Honeywell installed in the papermaking processes around the world commonly monitor at least basis weight, caliper, and moisture content. Although, the fuzzy control charts proposed in the present work can be used for any quality variable in papermaking, the implementation will be referred to paper moisture content data.

According to Tappi [T. Committee-00], the traditional process to determine paper moisture content by oven drying, needs to cut a paper profile from a rolling section (big reel) and quickly place it inside a bag. Then, the profile (sample) must be cut in small samples of one square foot or circles according to the corresponding laboratory equipment. When the samples are cut to a standard size, each sample's weight must be determined (wet weight), and after this step, all samples are placed for at least 60 minutes inside the oven, which must be calibrated at 105°C. After the time has elapsed, the samples are weighed again (dry weight) and the moisture content is calculated using a standard (3-51):

$$Moisture\ (\%) = \frac{Wet\ weight - Dry\ weight}{Wet\ weight} \tag{3-51}$$

As mentioned above, the company has three production lines: paper, corrugated cardboard boxes, and high graphic boxes. However, the proposed methodology was implemented in the plant that only includes the production lines for paper and corrugated cardboard boxes. By using this methodology, it is intended that most of the measurements detected as out of control by the traditional control charts, can be detected in control as much as possible mainly for moisture content. The proposal was aligned with the company´s continuous improvement policy.

The data collected for each paper roll include the model, month, date, shift, time, roll number, variable, and the measurements, as shown in Appendix C. The model refers to each type of paper, for instance, an L-200 means a 200-gram kraft liner paper, or a LC-240 means a 240-gram coated liner paper. The papermaking process take place during three shifts per day, and for every roll, a number is assigned from the first until the last day of the year, returning the count every start of the year.

To develop the fuzzy control charts, the data selected corresponds to the LC-240 paper during a 5-day period (June 8-12, 2019), as shown in Appendix C. By using from (3-8) to (3-10), the process data were converted to fuzzy numbers X. The results are shown in Table 3.1. The fuzzy moving range values (MR) used to determine the control limits are shown in Table 3.2. From this data, the fuzzy sample average ($\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c$) and the fuzzy moving range value ($\overline{MR}_a, \overline{MR}_b, \overline{MR}_c$) were calculated. These two fuzzy numbers are also the center lines of the fuzzy control charts

TABLE 3.1. FUZZY NUMBERS FOR THE MOISTURE CONTENT OF A LC-240 COATED PAPER

Roll #	X_a	X_b	X_c	Roll #	X_a	X_b	X_c
4657	4.7	5.0	5.3	4727	4.2	4.6	5.1
4658	4.7	5.1	5.4	4728	4.9	5.5	6.0
4659	4.7	5.1	5.5	4729	5.0	5.5	5.9
4660	4.9	5.1	5.4	4730	4.6	5.1	5.5
4661	4.9	5.2	5.4	4731	3.7	4.1	4.5
4662	4.4	5.0	5.6	4734	4.0	4.3	4.6
4663	4.8	5.0	5.1	4740	4.4	4.7	5.0
4664	3.9	4.5	5.1	4741	4.4	5.0	5.6
4665	3.6	4.1	4.5	4742	4.1	4.6	5.1
4666	4.2	4.5	4.9	4743	4.4	4.8	5.2
4667	4.2	4.6	4.9	4744	4.5	4.8	5.0
4668	4.2	4.6	4.9	4745	4.3	4.8	5.3
4669	4.2	4.6	5.0	4746	4.3	4.8	5.3
4670	4.2	4.6	5.2	4763	4.2	4.6	4.9
4671	4.1	4.6	5.1	4764	4.2	4.6	4.9
4672	4.5	4.9	5.3	4765	4.3	4.5	4.7
4673	4.4	5.0	5.5	4766	5.0	5.3	5.6
4674	4.1	4.6	5.1	4767	5.1	5.4	5.7
4675	4.0	4.6	5.1	4768	4.7	4.9	5.1
4676	4.0	4.6	5.1	4769	4.5	5.0	5.6
4677	4.3	4.6	4.8	4770	5.1	5.3	5.5
4678	4.3	4.5	4.7	4771	4.8	5.3	5.7
4679	4.2	4.6	5.0	4772	4.7	5.2	5.7
4680	3.7	4.3	4.8	4773	4.7	5.3	5.9
4681	3.9	4.2	4.5	4774	4.7	5.3	5.8
4682	3.6	4.2	4.8	4775	4.9	5.2	5.5
4725	4.4	4.6	4.8	4776	4.7	5.3	5.8
4726	4.3	4.5	4.8	4777	4.5	5.1	5.7

$(\widetilde{CL})$. The resulting values are: $(\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c) = (4.445, 4.807, 5.168)$ and $(\overline{MR}_a, \overline{MR}_b, \overline{MR}_c) = (0.183, 0.183, 0.183)$.

By employing equations from (3-11) to (3-16), the fuzzy upper, central, and lower control limits for FICC and FMRCC were calculated. Results are shown in Table 3.3.

When the fuzzy control limits have been calculated, then it is necessary to apply the defined α-cut. For this research, an α-cut of 0.5 is applied by using equations from (3-23) to (3-28), and the fuzzy control limits with the α-cut are calculated by equations from (3-29) to (3-34). The results are shown in Table 3.4.

Finally, the fuzzy midrange approach is applied to convert the α-cut fuzzy control limits to

TABLE 3.2. FUZZY MOVING RANGE VALUES

Roll #	MR_a	MR_b	MR_c	Roll #	MR_a	MR_b	MR_c
4657				4727	0.115	0.078	0.271
4658	0.033	0.067	0.101	4728	0.742	0.834	0.926
4659	0.036	0.026	0.088	4729	0.067	0.016	0.035
4660	0.153	0.032	0.088	4730	0.413	0.408	0.403
4661	0.039	0.025	0.011	4731	0.868	0.950	1.032
4662	0.478	0.158	0.162	4734	0.332	0.208	0.084
4663	0.338	0.042	0.422	4740	0.313	0.358	0.403
4664	0.809	0.425	0.041	4741	0.030	0.301	0.572
4665	0.300	0.433	0.566	4742	0.278	0.386	0.494
4666	0.549	0.435	0.321	4743	0.275	0.178	0.081
4667	0.033	0.040	0.047	4744	0.082	0.017	0.116
4668	0.012	0.004	0.004	4745	0.177	0.050	0.277
4669	0.008	0.037	0.066	4746	0.009	0.017	0.025
4670	0.039	0.017	0.073	4763	0.116	0.258	0.400
4671	0.092	0.033	0.026	4764	0.003	0.000	0.003
4672	0.404	0.325	0.246	4765	0.161	0.025	0.211
4673	0.128	0.051	0.230	4766	0.695	0.810	0.925
4674	0.260	0.376	0.492	4767	0.083	0.073	0.063
4675	0.129	0.021	0.087	4768	0.461	0.531	0.601
4676	0.068	0.013	0.042	4769	0.145	0.147	0.439
4677	0.281	0.025	0.331	4770	0.626	0.283	0.060
4678	0.033	0.058	0.083	4771	0.358	0.059	0.240
4679	0.124	0.092	0.308	4772	0.065	0.049	0.033
4680	0.450	0.325	0.200	4773	0.028	0.125	0.222
4681	0.227	0.033	0.293	4774	0.019	0.067	0.115
4682	0.333	0.033	0.267	4775	0.197	0.066	0.329
4725	0.776	0.400	0.024	4776	0.207	0.058	0.323
4726	0.095	0.053	0.011	4777	0.173	0.117	0.061

fuzzy values by equations from (3-35) to (3-37) and equations from (3-40) to (3-42) for FICC and FMRCC respectively. The results are shown in Table 3.5. Meanwhile, to calculate de fuzzy midrange values, the equations from (3-38) to (3-43) were used for the α-cut fuzzy individual and moving range numbers respectively. The results are shown in the Appendices D and E.

Therefore, to conclude the process situation, (3-39) was used for the FICC, meanwhile, (3-44) was used for the FMRCC. The process situation (in control or out of control) for each sample are shown in the Appendices D and E respectively. In addition, the fuzzy midrange values for proposed fuzzy individual control chart are shown in Fig. 3.3. Meanwhile, the fuzzy midrange values for the fuzzy moving range control chart are shown in Fig. 3.4.

The traditional individual control charts have been developed by using the process data and

TABLE 3.3. FUZZY CONTROL LIMITS FOR FICC AND FMRCC

Control Limits	$\bar{\bar{X}}_a$	$\bar{\bar{X}}_b$	$\bar{\bar{X}}_c$	$\overline{MR}_a$	$\overline{MR}_b$	$\overline{MR}_c$
$U\tilde{C}L$	5.046	5.292	5.855	0.788	0.597	0.794
$\widetilde{CL}$	4.404	4.807	5.209	0.241	0.183	0.243
$L\tilde{C}L$	3.763	4.321	4.562	0.000	0.000	0.000

TABLE 3.4. FUZZY CONTROL LIMITS WITH α-CUT OF 0.5

Control Limits	$\bar{\bar{X}}_a^\alpha$	$\bar{\bar{X}}_b^\alpha$	$\bar{\bar{X}}_c^\alpha$	$\overline{MR}_a^\alpha$	$\overline{MR}_b^\alpha$	$\overline{MR}_c^\alpha$
$U\tilde{C}L$	5.169	5.292	5.574	0.692	0.597	0.696
$\widetilde{CL}$	4.605	4.807	5.008	0.212	0.183	0.213
$L\tilde{C}L$	4.042	4.321	4.441	0.000	0.000	0.000

TABLE 3.5. CONTROL LIMITS BY USING THE FUZZY α-CUT MIDRANGE APPROACH OF 0.5

FICC Limits	Values	FMRCC Limits	Values
UCL_{mr-X}^{α}	5.372	UCL_{mr-MR}^{α}	0.694
CL_{mr-X}^{α}	4.807	CL_{mr-MR}^{α}	0.212
LCL_{mr-X}^{α}	4.242	LCL_{mr-MR}^{α}	0.000

moving ranges shown in the Appendix F. By using equations from (3-45) to (3-50), the control limits for the individual and moving range control charts were calculated. The results are shown in Table 3.6. Thus, the process situation is shown in Appendices G and H, meanwhile, the individual and moving range control charts are shown in Fig. 3.5 and Fig. 3.6.

By applying the fuzzy individual control chart approach, only 7 “out of control” values were observed (the results are shown in Appendix D), while by applying the traditional individual control chart procedure, 12 “out of control” values were observed (the results are shown in Appendix G). Whereas for the fuzzy moving range control chart approach, 3 “out of control” values were observed (the results are shown in Appendix E), while, by applying the traditional moving ranges control chart approach, 4 “out of control” values were observed (the results are shown in Appendix H). Therefore, the main advantage of using the proposed fuzzy individual control chart is related to its ability to detect paper rolls “in control”. Fig. 3.3 shows that the paper

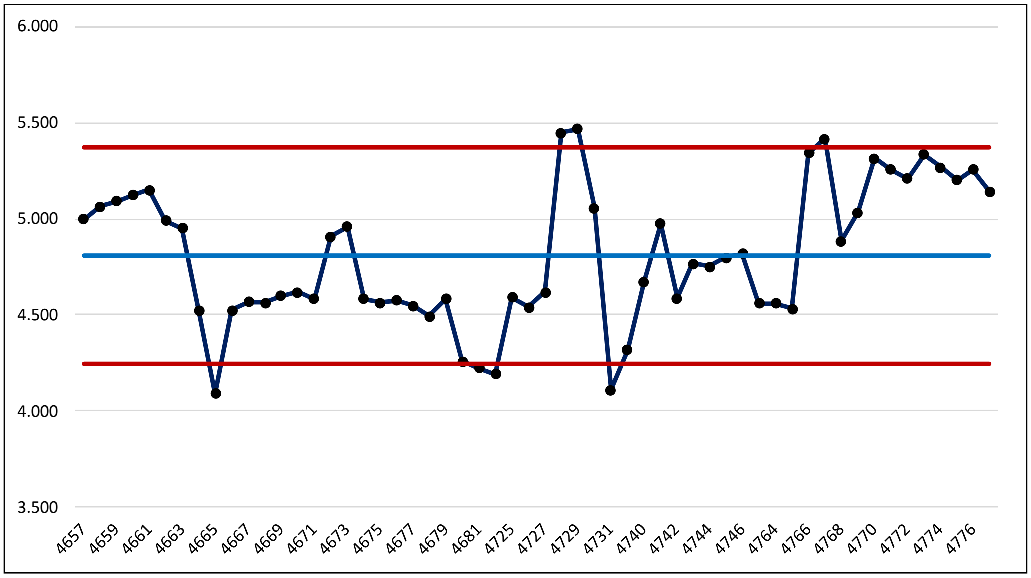


Fig. 3.3 Fuzzy individual control chart (FICC) for $\alpha = 0.5$.

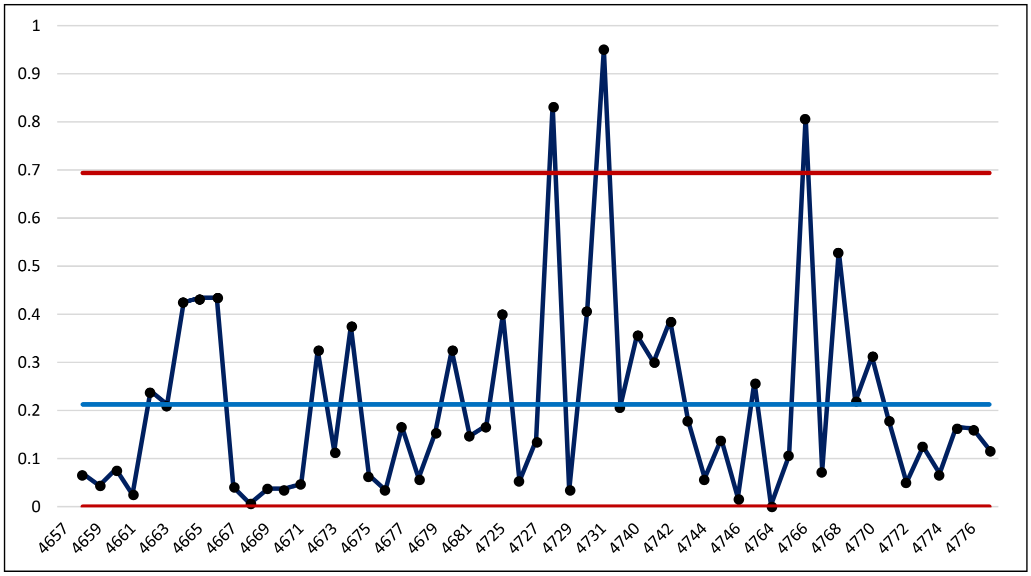


Fig. 3.4 Fuzzy moving range control chart (FMRCC) for $\alpha = 0.5$.

rolls detected as "in control" were 4680, 4734, 4766, 4770, and 4773. Meanwhile, the same paper rolls were detected as "out of control" as shown in Fig. 3.5. When comparing the fuzzy moving range control chart, the advantage is like the fuzzy individual control chart. In this case, Fig. 3.4 shows that the paper roll detected as "in control" was 4764; meanwhile, the same paper roll was detected as "out of control", as shown in Fig. 3.6.

The fuzzy individual and moving range control charts showed greater amplitude than the traditional control charts, with an amplitude of 1.130 in the fuzzy individual control chart, against

TABLE 3.6. CONTROL LIMITS BY USING TRADITIONAL INDIVIDUAL CONTROL CHARTS (ICC)

ICC Limits	Values	MRCC Limits	Values
$U\tilde{C}L_{\bar{X}}$	5.292	$U\tilde{C}L_{MR}$	0.597
$\widetilde{CL}_{\bar{X}}$	4.807	$\widetilde{CL}_{MR}$	0.183
$L\tilde{C}L_{\bar{X}}$	4.321	$L\tilde{C}L_{MR}$	0.000

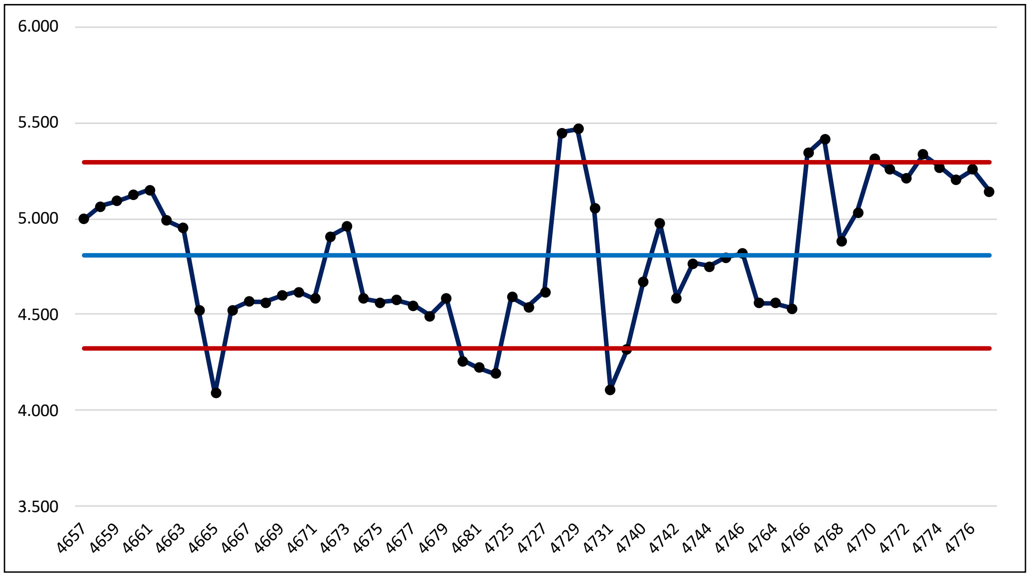


Fig. 3.5 Traditional individual control chart (ICC).

0.972 in the traditional individual control chart. While, the amplitude observed in the fuzzy moving range control chart was 0.694 against 0.597 in the traditional moving range control chart.

By implementing the proposed equations to calculate the fuzzy numbers, the α-cut and the control limits are calculated with the extreme numbers of the triangular function, and thus, greater amplitude is achieved, unlike traditional control charts, where the control limits are calculated with point values. In addition, the risk of rejecting batches of paper rolls decreases (depending on the sampling criteria) since a greater number of paper rolls will be under control. Moreover, the increased amplitude in the proposed fuzzy control charts is not considerable enough to affect the corrugated process, at least for out of specification problems caused by paper moisture content.

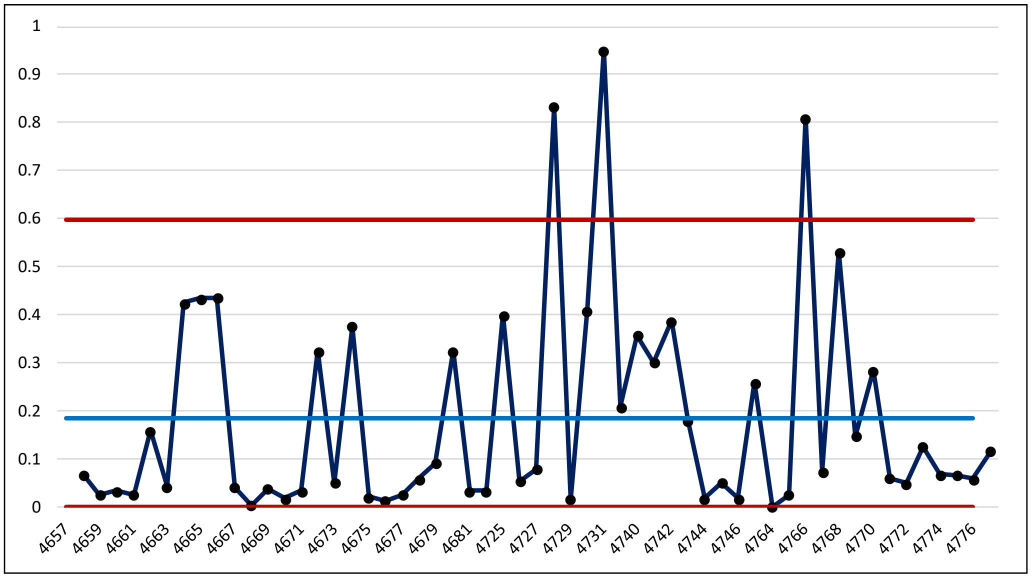


Fig. 3.6 Traditional moving range control chart (MRCC).

3.4. Conclusions

The moisture content of paper is a critical quality characteristic that must be monitored, for both, the papermaking and corrugated processes. Currently, in the papermaking process, the paper moisture content and other important quality characteristics are monitored by using traditional control charts. However, due to the paper's hygroscopic characteristics, this monitoring approach is not the best option because a small shift in moisture content may send the measure above or below of the upper and lower control limits respectively, and therefore it will be detected "out of control".

The present research aimed to propose a new methodology to develop a fuzzy control chart for individual measurements. The proposed method to generate fuzzy numbers is very useful because it is based on the sigma level of the process and the variation observed in the sample, which can be adapted to any type of process.

One of the most significant findings from this study is that the proposed fuzzy individual and moving range control charts are more flexible because the amplitude between the upper and lower control limits is greater than those shown by the traditional individual control charts. By increasing the amplitude, then false alarms could be prevented due to the uncertainty coming from the measurement system or the nature of the process.

The proposed methodology results showed that the fuzzy individual and moving range control charts can detect fewer real “out of control” measurements than the traditional individual and moving range control charts, demonstrating the advantage and the flexibility of the proposed methodology.

Although, the fuzzy midrange approach with an α-cut value of 0.5 showed good results, further research, could also be conducted with different α-cut levels to measure its effect on the amplitude between the upper and lower control limits. Since the results have been satisfactory, an Excel based-software tool of the proposed fuzzy control charts will be developed to its implementation in the papermaking process.

Besides, since the fuzzy control charts proposed in this work found fewer real “out of control” measurements, this approach should reduce the probability of making Type I error, rejecting good product, however, their quantification would be carried out in future research.

4. Alternative Method for Determining Basis Weight in Papermaking by Using an Interactive Soft Sensor Based on ANN Model

Currently, there are two procedures to determine the paper basis weight in the papermaking processes: the methods used by the paper quality control laboratory and the measurements made by the quality control system (QCS). This chapter presents an alternative to estimate the basis weight for any papermaking process founded in an artificial neural network model. The neural network architecture was constructed by trial and error, obtaining the best results with the 24 input variables (independent variables) in the first layer, two hidden layers with 48 and 12 neurons, respectively, and one response variable (dependent variable) in the last layer. The rest of the hyperparameters used for training and validation were MAE (mean absolute error) and MAPE (mean absolute percent error) for the loss and metric functions respectively, RMSprop optimizer, a batch size of 32, and 1,000 epochs. The training, validation, and testing process was performed in Python. The findings indicate that the model can determine the basis weight in papermaking processes with reasonable accuracy given the dependent variables analyzed in this research. The explained variance score reached by the model was 94% (accuracy level), and the mean absolute error was 12.40 grams/m^2. Besides, to validate the method performance, a large dataset not included in building the proposed model was used. The results show a mean absolute error of 12.10 grams/m^2. Finally, the model was inserted in a user interface developed in Python[3] using the streamlit app. This GUI will be an alternative to the current methods to determine the basis weight of the paper.

4.1. Introduction

It is a standard practice to take measurements of product characteristics, either of a variable or attribute type, to study specific processes by changing different variables suspected of contributing to the process variation. The resulting data are then analyzed in a certain way to

[3] Python, Version 3.8.5, Python Software Foundation, 2021.

determine if the changes occurred in these variables have had a significant effect either scientifically or economically [Kim-19]. The papermaking processes are no exception since these processes have multiple variables that affect product quality, such as basis weight, caliper, moisture content, ash content, and fiber orientation [Merbold-16], to mention a few. In addition, whiteness is an essential property of coated paper [Tarasov-18]. Therefore, it is vital to monitor these variables to identify the significance differences in reducing process or product variation and successfully improving product quality.

The traditional control chart technique has been widely used in different industries [Camargo-10; Dudek-Burlikowska-05; Rodríguez-Álvarez-21a; Shamsuzzaman-15; Zaman-20; Zhiyuan-15]. Although, the fuzzy set theory proposed by [Zadeh-65] has also been employed for at least three decades to develop control charts based on this theory [Chang-96; Cheng-05; Gülbay-06; Gülbay-07; Kaya-11a; Shu-11]. However, these approaches do not relate the operating conditions to the output variables (quality characteristics), being one of their main disadvantages. As alternative, regression models are tools that relate input to output variables and have been widely used for predictive and process optimization purposes in the pulp and paper industry. For instance, Adamopoulos et al. [Adamopoulos-16] presented a predictive model for the mechanical properties of corrugated base papers from fiber and physical property data using multiple linear regression and artificial neural networks. Kilulya et al. [Kilulya-15] used a partial least squares (PLS) regression model to evaluate the effects and influence of the lipophilic extractive residues on quality parameters of dissolving pulp. Their findings indicate that sterols, fatty alcohol, saturated and unsaturated fatty acids significantly influenced/affected viscosity, kappa number, and carbohydrates in the pulp. Meanwhile, Marklund et al. [Marklund-98] modeled the influence of fiber properties on strength parameters for softwood kraft made from 20 different wood samples by using multivariate data analysis and partial least squares method. Recently, Rodriguez et al. [Rodriguez-Alvarez-21a] used a regression tree model and experimental designs to find optimal operating conditions in the papermaking machine's complex rodsizer and spooner section.

On the other hand, neural networks models have demonstrated almost the same or more predictive capability than traditional techniques [Costela-20; Mahmoud-21; Mohammadi-21; Saha-21; Shams-21]; however, this approach has not been widely investigated to determine quality characteristics in papermaking processes.

ABB and Honeywell (companies dedicated to the sale of technology solutions for the pulp and paper industry) contribute to solutions based on data analysis oriented to the optimization and control of processes in various industries like the pulp and paper industry. For example, ABB is a leader in the papermaking market by offering a wide range of innovative products for paper quality measurements, ranging from in-line scanning to test laboratories [ABB-21]. Among its robust solutions is a quality management system through its Quality Control System (QCS), while Honeywell offers a similar product with its Quality Control System 4.0 [HONEYWELL-21].

The QCS is reliable to monitor variables for quality assurance purposes. It keeps the output variables (base weight, caliper, and moisture content mainly) under control since the values of the input variables (process) are being always controlled. However, one of the significant disadvantages of these control systems is the self-calibration process, since, at time intervals defined by the supplier and/or process characteristics. The system must to go offline to perform the self-calibration and/or maintenance process. Thus, leave the control in manual mode and loss of visibility of the behavior of the output variables. During this time, the system is off-line, and many linear meters (depending on the speed of the machine) may not be within specification.

Currently, ABB offers a solution for monitoring basis weight by virtually measuring the weight of the paper. If the QCS is offline, their approach helps operators keep the basis weight properties within target by creating an initial static conditional weight model using historical data and thus establish an initial expectation of the accuracy of the calculated basis weight. If the accuracy of the initial model is acceptable, then the calculated basis weight measurement is implemented online through their platform called ABB AbilityTM. However, this solution is intended to be used for output variable monitoring purposes while the QCS is offline and is not intended to be used for experimental purposes.

Machine learning techniques are widely used in many industrial applications [Morala-21], including experimental designs [Wong-18; Heinisch-21; Moreira-21; Mezgár-97]. In addition, several authors have worked with interactive user tools called soft sensors [Zeng-21; Kamyar-21; Niño-Adan-21; Chang-21], which are employed as tools for visualization output data from the developed models. However, there is no evidence in the use of the development of such interactive tools to determine basis weight in papermaking processes.

Since there are only two approaches to determine basis weight in papermaking processes, this research presents a novelty model based on data science techniques to determine basis weight as an alternative to the current methods. The proposed method is based on neural networks due to its predictive capability over the building process, its predictive ability using data not included in the building process, and this method has not been investigated in its current form to evaluate process performance based on capability indices.

In addition, the model will be embedded in a graphic user interface; thus, the user will be able interact by entering input variables values (process variables) and estimate with reasonable accuracy the basis weight value (output variable). Hence, the proposed method is an excellent alternative to the existing ones. Furthermore, the model could be used to perform experimental designs aimed at finding optimal operating conditions.

This chapter is organized as follows: Section II presents a brief review of neural networks architectures, including the common hyperparameters used to develop a model based on the neural networks approach. Section III presents the methodology, which corresponds to the phases of a typical data science project. Finally, the last two sections include the results, analysis, conclusions, and future research.

4.2. Neural Networks Architectures: A Brief Review

For a few decades until now, artificial neural networks constitute one of the most important computational intelligence tools being used in a wide variety of problems [Haykin-04]. The first appearance on literature of ANNs dates back to 1943 when McCulloch and Pitts [McCulloch-43] created a simple neural network computing model. However, until 1949 the first learning rules were introduced by Hebb [Hebb-05]. Since that, ANNs have experienced a rapid growth. The Perceptron is one of the simplest ANN architectures, invented in 1957 by Frank Rosenblatt [Rosenblatt-57].

The neural systems are intense nonlinear signal processors; however, the results are regularly a long way from satisfactory [Rosli-16]. Two of the essential criteria in building up a neural system model are network architecture and parameter selection. The neurons interconnected structure defines the network architecture in an artificial neural network. Thus, the number and type of neurons connectivity and the activation function are essential parameters, and their selection is determinant to produce a good network for any case study [Karamichailidou-21].

Several neural systems architectures are available in the literature [Karayiannis-92; Fausett-06; Dayhoff-90; Teuscher-12]. In the present work, we describe in detail the two most

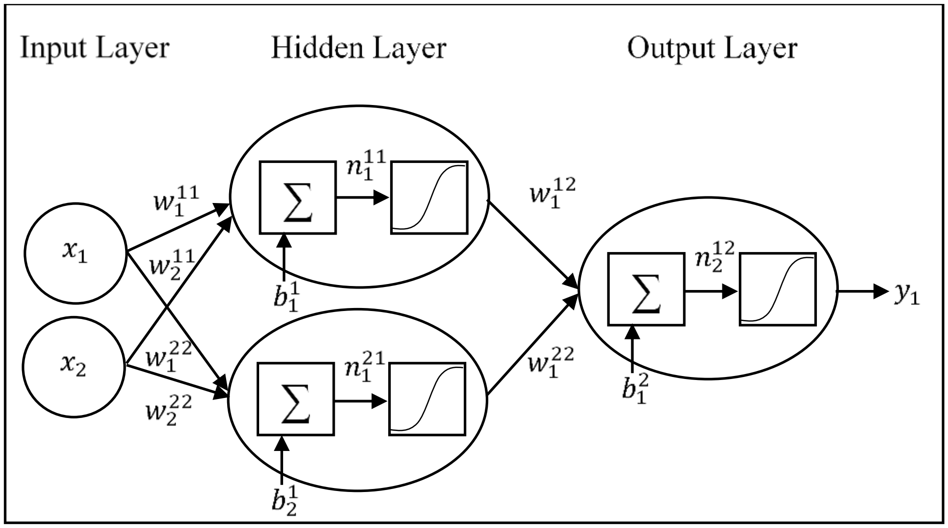


Fig. 4.1 The architecture of MLP-NN (taken from [Rosli-16]).

common architectures: the multilayer perceptron neural network (MLP-NN) and radial basis function neural network (RBF-NN), and, briefly, the generalized regression neural network (GR-NN) and Elman neural network (Elman-NN).

4.2.1 Multilayer Perceptron Neural Network

One of the most well-known architectures used by researchers has been the multilayer perceptron (MLP). This architecture includes the input layer, hidden layer(s), and output layer. The architecture is shown in Fig. 4.1. This approach is essentially a combination of neurons, biases assigned to neurons, interconnections among them, and weights assigned to these interconnections. The learning process is performed according to input and target data sets and training algorithms [Hashemi-Fath-20].

Mathematically, a neuron K can be defined via (4-1) and (4-2).

$$y_k = f(\mu_k + b_k) \tag{4-1}$$

$$\mu_k = \sum_{i=1}^{N} w_{ki} x_i \tag{4-2}$$

where $x_1, x_2, x_3, \ldots, x_n$ denote the input signals, $w_{k1}, w_{k2}, w_{k3}, \ldots, w_{kn}$ are the connection weights of the neuron, μ_k is the linear output of the linear combination among weighted inputs, b_k is the bias term, f is the activation function, and y_k is the output signal of the neuron.

On the other hand, if a MLP-NN with two hidden layers is going to be used. To illustrate this scenario, in [Wei-22] is reported a study on predictive relationships between measured color and four control factors of PolyJet (i.e., three RGB values of specified color and finish type) by design of experiments and application of multilayer perceptron (MLP) neural network model. Mathematically, the i^{th} neuron in the second layer is calculated by (4-3).

$$a_i^2 = g(\sum_i w_{ij}^1 x_j + b_i^2) \tag{4-3}$$

where g is the activation function, w_{ij}^1 is the weight allocated to the edge between the j^{th} input and the i^{th} neuron, and x_j, is the j^{th} input. Meanwhile, b_i^2 is the bias assigned to the neuron.

Similarly, a neuron in the third layer is calculated by (4-4).

$$a_i^3 = g(\sum_i w_{ij}^2 a_j^2 + b_i^3) \tag{4-4}$$

where a_i^3 is the i^{th} neuron in the third layer, and a_j^2 is the j^{th} neuron in the second layer. Lastly, an output response in the output layer is calculated by (4-5).

$$y_i = \sum_j w_{ij}^3 a_j^3 + b_i^4 \tag{4-5}$$

where y_i is the i^{th} output response, and a_j^3 is the j^{th} neuron in the third layer.

The multilayer perceptron is trained based on the backpropagation algorithm, which follows a learning procedure based on the error-correction rule. By comparing the target values and the output of the network, the error value is calculated. Afterward, the weights and biases are adjusted to minimize the error, and the training process continues until the network reaches a predefined minimum allowable error. The error function typically used is the mean square error (MSE) [Hashemi-Fath-20], but in the presence of many outliers in the training set, it is recommended to use the mean absolute error (MAE) [Géron-19].

4.2.2 Radial Basis Function Neural Network

The radial basis function is widely used by many researchers in various sciences, mainly as function approximation and pattern classification [Fu-03; Moody-89; Nabney-99; Poechmuelloer-94]. This network is easy to train, design, and robust tolerance to input noise [Rosli-16; Hashemi-Fath-20].

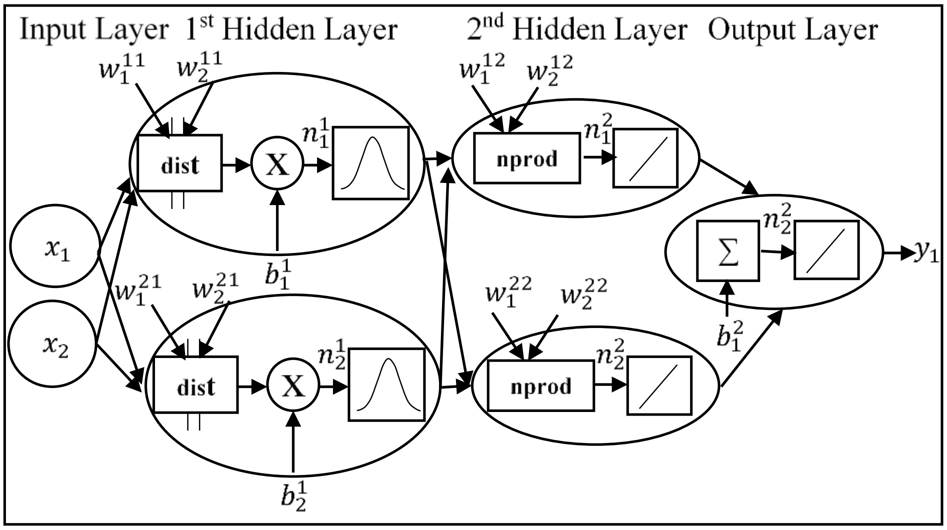


Fig. 4.2 The architecture of the RBF-NN (taken from [Rosli-16]).

This This neural network architecture comprises three layers, namely an input layer, a hidden layer, and an output layer. The input layer serves only as an input distributor to the hidden layer. The hidden layer contains radial basis functions, and the output layer generates the network output by linearly combining the outputs of the hidden neurons [Hashemi-Fath-20]. The architecture is shown in Fig. 4.2.

The formulation of a radial basis function neural network is presented in (4-6).

$$y_i(x) = \sum_{j=1}^{k} w_{ij} \emptyset\left(\left\|x - c_j\right\|\right) \tag{4-6}$$

where x is the input vector, y_i is the network's *i*th output, *K* is the number of neurons in the hidden layer, C_j denotes the center of the *j*th hidden neuron, w_{ij} represents the weight of the link from the *j*th neuron in the hidden layer to the *i*th neuron in the output layer, and $\|.\|$ is the Euclidian norm. While, $\emptyset$ is the radial basis function used in the neurons of the hidden layer. This parameter is a multidimensional radial basis function describing the difference between an input vector and a pre-defined center vector.

The most common applications in literature are referring to the Gaussian Function defined in (4-7).

$$\emptyset\left(\left\|x - c_j\right\|\right) = e^{-\left(\frac{\left\|x-c_j\right\|^2}{2\sigma_j^2}\right)} \tag{4-7}$$

where σ_j is the width of the *j*ht hidden neuron. By finding the centers, widths, and the weights connecting hidden neurons to the output is the key for constructing and training the radial basis function neural network.

4.2.3 Generalized Regression and Elman Networks

Other types of neural network architectures are the generalized regression and Elman neural networks. The generalized neural network has seldom been employed for addressing nonlinear process monitoring issues [Lan-20]. However, due to its strong nonlinear mapping capability, simplicity of the structure, and high robustness, the generalized regression neural network has been demonstrated to be a powerful tool for nonlinear supervised learning [Baruník-16]; furthermore, it can be trained to estimate the behavior of complex systems with a non-parametric technique [Antanasijević-15]. Treated as normalized [Konate-15], this approach belongs to a category of radial basis function neural networks, but it can perform fast learning and coverage to the optimal regression surface quickly [Specht-91], even when the number of training samples is limited [Amiri-10].

The generalized regression neural network architecture consists of four layers: the input, hidden, summation, and output layers, respectively. The process from the originating neurons is multiplied by their weights at each hidden neuron [Rosli-16]. The weights are added with a bias to increment or decrement the input that goes into the activation function defined [Rooki-16].

Finally, the Elman neural network proposed by J. L. Elman in 1990 [Elman-90] is a kind of feedforward neural network which is especially suitable for time series prediction. This approach better predicts performance because it has a load-bearing layer that other neural networks do not have. This approach can be regarded as a recurrent neural network with a local memory unit and local feedback connection [Zhao-20]. This is one of its main advantages.

The Elman neural network architecture consists of two layers. A feedback connection is formed by feeding the output of the hidden layer back to the input layer referred to as context layer [put reference from neural network architecture]. A feedback loop with a single delay stores the information and retains the memory [Sundaram-16]. Its structure is made simple, and the input parameters are minimized, thereby shortening the training time [Sun-15].

4.2.4 Neural Networks Hyperparameters

As it is well-known, multilayer perceptron can be used for regression tasks. If it is necessary to predict a single value, then just need a single output neuron; thus, the output is the predicted value. When building an MLP for regression, it is unnecessary to use an activation function for the output neurons, so they are free to output any range of values. However, if it is required to guarantee that the output will always be positive, then the rectified linear unit activation function can be used [Géron-19].

There are many hyperparameters when a neural network is designed. For instance, in a simple MLP, the number of layers, the number of neurons per layer, the type of activation function to use in each layer, the weight initialization logic, and much more can be changed. Hyperparameter tuning is still an active area of research. Recently, Max Jaderberg et al. [Jaderberg-17] have work on this topic.

For the number of hidden layers, a common practice is selecting a single hidden layer for many problems. Currently, it has been shown that an MLP with just one hidden layer can model even the most complex functions provided it has enough neurons. These facts convinced researchers that there was no need to investigate deeper neural networks for a long time. However, deep networks have a much higher parameter efficiency. It is better to start with just one or two hidden layers for some problems, and it will work just fine [Géron-19].

The type of input determines the number of neurons per hidden layer and output required. A common practice is to form a pyramid, with fewer and fewer neurons at each layer, the rationale being that many low-level features can coalesce into far fewer high-level features. As for the number of layers, users can increase the number of neurons until the network starts overfitting. In general, the user will get more bang for the buck by increasing the number of layers than the number of neurons per layer. Unfortunately, as can see, finding the perfect number of neurons is still somehow a dark art.

The learning rate is arguably one of the most critical hyperparameters. In general, the optimal learning rate is about half of the maximum learning rate. Then, a simple approach for tuning the learning rate is to start with a large value that makes the training algorithm diverge, divide this value by 3, try again, and repeat until the training algorithm stops diverging.

Training a vast deep neural network can be painfully slow. So, choosing a better optimizer is also vital to deal with this possible problem. Four ways to speed up training are common: applying a good initialization strategy for the connection weights, using a good activation function, batch normalization, and reusing parts of a pre-trained network. However, another considerable speed boost comes from using a faster optimizer. The most used in practice are momentum optimization, Nesterov accelerated gradient, AdaGrad, RMSProp, and Adam and Nadam optimization [Géron-19].

Another hyperparameter is the batch size, which significantly affects the model's performance and training time. In general, the optimal batch size will be lower than 32. A small batch size ensures that each training iteration is very fast, and although a large batch size will give a more precise estimate of the gradients. A common practice is the use of a batch size greater than 10. In addition, an issue related to training iterations does not need to be tweaked: just use early stopping instead.

Finally, it has been well recognized that the type of activation functions plays a crucial role in the multi-stability analysis of the neural network. Different activation functions might lead to other equilibrium points and different dynamical behaviors of neural networks [Nie-19]. The common activation functions available are relu (rectified linear unit), sigmoid, softmax, softplus, softsign, tanh (hyperbolic tangent), selu (scaled exponential linear unit), elu (exponential linear unit), and exponential.

Many practical recommendations for deep networks are presented in 2012 [Bengio-12].

4.3. Methodology

For developing the interactive soft sensor, the present chapter will follow the common process of a data science project: frame the problem, collect raw data, process the data, explore the data, perform in-depth analysis, and communicate the results.

4.3.1 Frame the Problem

Beyond the methods used by the quality control laboratory and the quality control system (QCS) measurements available on the market, there are no alternatives to determine the basis weight of the paper in the papermaking processes. So, in the present chapter, we intend to develop a novelty model based on data science techniques to estimate the basis weight in papermaking processes. In addition, a graphical user interface will be developed so that the user can interact by entering values of the input variables (process variables) and calculate with acceptable precision the value of the basis weight (output variable).

4.3.2 Raw Dataset Collected

The most common output variables monitored in papermaking machines are the basis weight, caliper, and moisture content. These variables are automatically monitored through a scanner. Basis weight and moisture content are included in the database [Raunio-18].

The database was collected on a 6-meter wide papermaking machine containing the three forming tables (top, middle, and back). This papermaking machine works all year round, shutting down only when there is scheduled maintenance or a process problem. The dataset includes the independent variables monitored the process, to maintain under control and specification the basis weight variable.

The complete dataset is a matrix of 342,501 rows by 43 columns. This dataset was extracted from the server that stores historical data and covers January 01 to August 30, 2019. This period includes all product grades (paper basis weights) that are manufactured in the process. The dataset was the readings taken by sensors at 1-minute time intervals in this period. The readings correspond to the main factors affecting the paper's basis weight (dependent variable, *y*) of the paper: flow rates, consistencies, storage tank levels, output pressures, lip angle, and machine speed (independent variables, *x's*).

4.3.3 Processing the Data

A first data cleaning operation was performed in Excel to eliminate all those data and/or variables that do not affect the basis weight of the paper. From the original dataset, a total of eighteen columns were removed. Remaining twenty-five defined columns. One of variables corresponds to the base weight (dependent variable), and the remaining twenty-four are distributed among flows, consistencies, pressures, levels, machine speeds, and lip position, being these the independent variables.

A second data cleaning operation was carried out with Excel to remove all data readings with no logic. First, all negative and zeros values were removed because the process studied does not produce thin paper grades (basis weight). Only readings equal to or greater than a basis weight of 100 grams (dependent variable) are included. Finally, because basis weight is determined mainly by machine speed, only data readings obtained equal to or greater than 50 meters per minute were included.

4.3.4 Explore the Data

In the presence of null data, these will be imputed with the average value of each column (variable) that has shown at least one null data (rows).

As an ideal tool for machine learning developments, the TensorFlow library (included in Python programming language) will be checked to identify a model capable of determining the basis weight of the paper with reasonable accuracy.

4.3.5 Perform In-depth Analysis

In this chapter, the artificial neural network (ann) approach will be used to identify the model with good accuracy (at least an R-Square of 90%). At a minimum, the ann network architecture comprises hidden layers, neurons, and activation functions [Rosli-16]. A common, well-known network architecture was the multilayer perceptron (MLP) system. MLP is one of the favored neural system topologies of most analysts [Sharma-15]. These networks are essentially a combination of neurons, biases assigned to neurons, interconnections or links among them, and weights assigned to these interconnections. The learning process is performed according to input and target data sets and training algorithms [Hashemi-Fath-20]. Although, for many years researchers struggled to find a way to train MLPs, in 1986 David Rumelhart, Geoffrey Hinton and Ronald Williams published a groundbreaking paper introducing the backpropagation training algorithm, which is still used today [Rumelhart-85].

Since the multilayer perceptron (MLP) is simpler to design, faster to train, the knowledge is already well spread throughout different scientific communities [Canário-20], and mainly due to its straightforwardness and capacity to predict precisely for exactly a regression scenario. Therefore, in the present work, the multilayer perceptron was selected as a baseline over other advanced strategies.

Firstly, the multilayer perceptron will be developed by following the sequential model. This is the most straightforward neural network model composed of a single stack of layers connected sequentially [Géron-19]. Each layer will be of Dense type; that is, they will be fully connected layers.

The rectified linear unit activation function (relu) will be used for each layer to guarantee that the output will always be positive. Gather to the number of neurons per hidden layer, a common practice is to size them by forming a pyramid. However, a rhombus shape is proposed in the present work. Thus, the shape of the input data is a 24-dimensional vector with a 48-dimensional output vector. The next layer has a 12-dimensional output vector, and finally, the 1-dimensional output vector corresponds to the response value.

The RMSProp will be used as an optimizer learning rate. The main gist of this algorithm is to maintain a moving (discounted) average of the square of gradients and divide the gradient by the root of this average [Hinton-12]. The mean absolute error (MAE) and mean absolute percentage error (MAPE) are considered the most proper for the loss and metric functions. In addition, the mean absolute error (MAE), the root mean square error (RMSE), and the explained variance score (R-Sq) would be calculated to evaluate performance in the building process of the model.

A total of 182,834 rows will be used in the building process of the model. Seventy-five percent for training, fifteen percent will be used for validation, and ten percent for testing. A batch size of 32 will be used in the present work.

Related to the training iterations (epochs) and trying to find an inflection point, a total of 1000 epochs will be used for the training process. Finally, to validate the method performance, a large dataset not included in building process of the proposed model will be used.

The neural network model for determining the basis weight in papermaking processes and the performance evaluation of the model will be carried out in Python programming language by using the TensorFlow 2.0 library.

4.3.6 Communicate Results

Since the neural network model developed is intended to be an alternative tool to determine the basis weight in papermaking processes. Therefore, a user interface will be developed in Python by using the streamlit app to enter the input variables data and know with reasonable accuracy the basis weight for any paper grade.

4.4. Results

By using the collected data as described above, in this section is presented the results of the model and graphic user interface developments.

4.4.1 Model Development

The model development follows the common data science process. The dataset collected included all paper grades, so, the period was adequate to develop a robust model. After the cleaning process applied to the dataset, the size of the resulting matrix was 215,103 rows by 25 columns. A total of fifteen percent of the dataset was extracted to perform different analyses using the proposed model. Therefore, these data were not included in the training, validation, and testing process.

The independent variables that showed the presence of null data were: consistency of output at machine head top, consistency of output in mixing tank top, consistency of output at machine head middle, consistency of output in mixing tank middle, consistency of output at machine head back, and consistency of output in mixing tank back. These null data were imputed with the following average values: 4.12, 4.00, 3.84, 3.60, 2.92, and 3.80.

After the cleaning process, the whole dataset was segregated into two arrays. An input array size of 164,550 rows by 25 columns was used in the training and validation process, while, an input array size of 18,284 rows by 25 columns was used in the test process.

For the neural network architecture design, the activation functions and the number of neurons per layer were being moved by trial and error. So, the best architecture and structure of the final neural network are shown in Table 4.1.

Using the loss and metric functions described above, a learning rate of 0.001 for RMSprop optimizer, a batch size of 32, and 1,000 epochs, the resulting mean absolute error (MAE) was 12.40 grams/m^2. In addition, the explained variance score (R-Sq) was 94%. Fig. 4.3 shown a training summary for the model loss level. While n Fig. 4.4 is shown the predicted vs. test data to evaluate the model performance in the building process of the model. The results show that the

TABLE 4.1. NEURAL NETWORK ARCHITECTURE

Model: "sequential"		
Layer (type)	Output Shape	Param #
dense (Dense)	(None, 48)	1,200
dense_1 (Dense)	(None, 12)	588
dense_2 (Dense)	(None, 1)	13
Total params: 1,801 Trainable params: 1,801 Non-trainable params: 0		

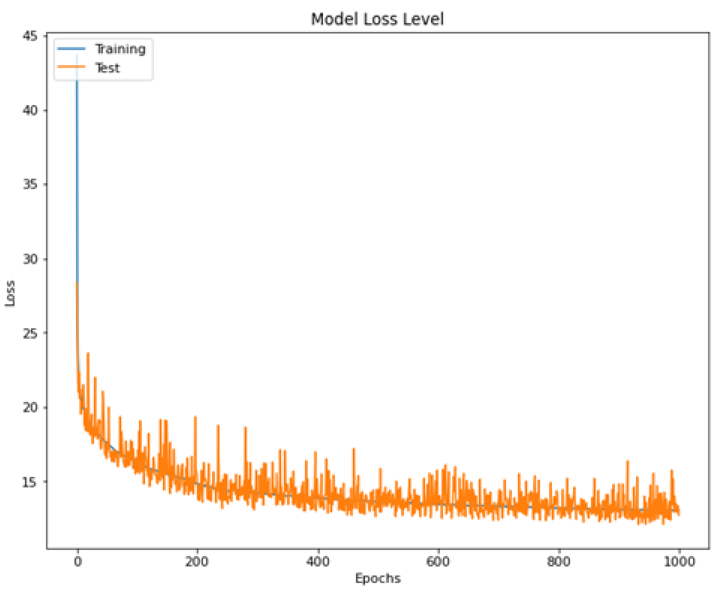


Fig. 4.3 Training summary of the model loss level.

model developed can determine the basis weight as an alternative to the quality control laboratory and the measurements made by the quality control system (QCS) available on the market. Appendix I presents two additional figures to show in detail the predicted vs. test data for two different samples ranges.

Finally, an external dataset not included in the building process of the model was used to validate the method performance. The dataset used here corresponds to the paper grades from 180 to 250 grams/m^2. These are the most common manufactured paper grades. The input array size was 7,768 rows by 24 columns, while the output array size was 7,768 rows by 1 column. The

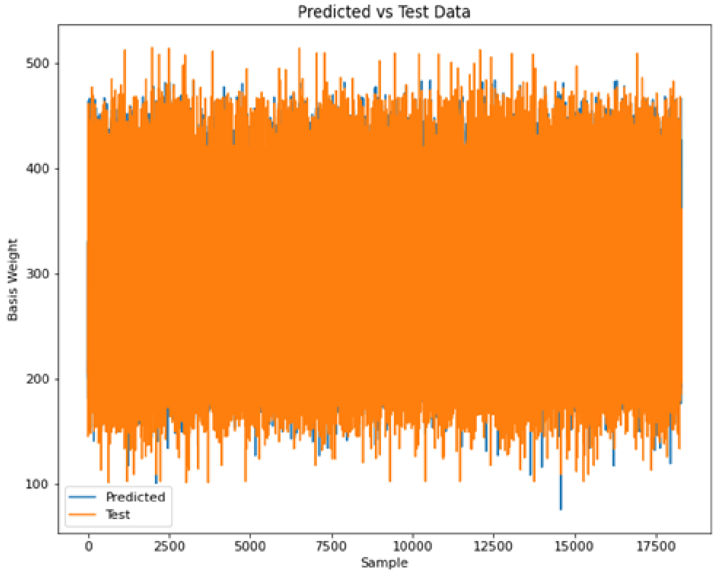


Fig. 4.4 Model performance: predicted vs test data.

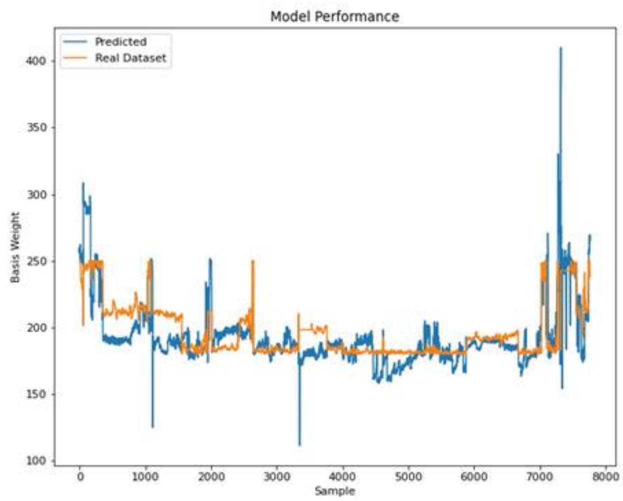


Fig. 4.5 Model performance with external dataset.

results are shown in Fig. 4.5 Fig. 4.5is shown the model performance by comparing the predicted values against the real dataset selected for this purpose. The results show a mean absolute error (MAE) of 12.10 grams/m^2.

4.4.2 Graphic User Interface

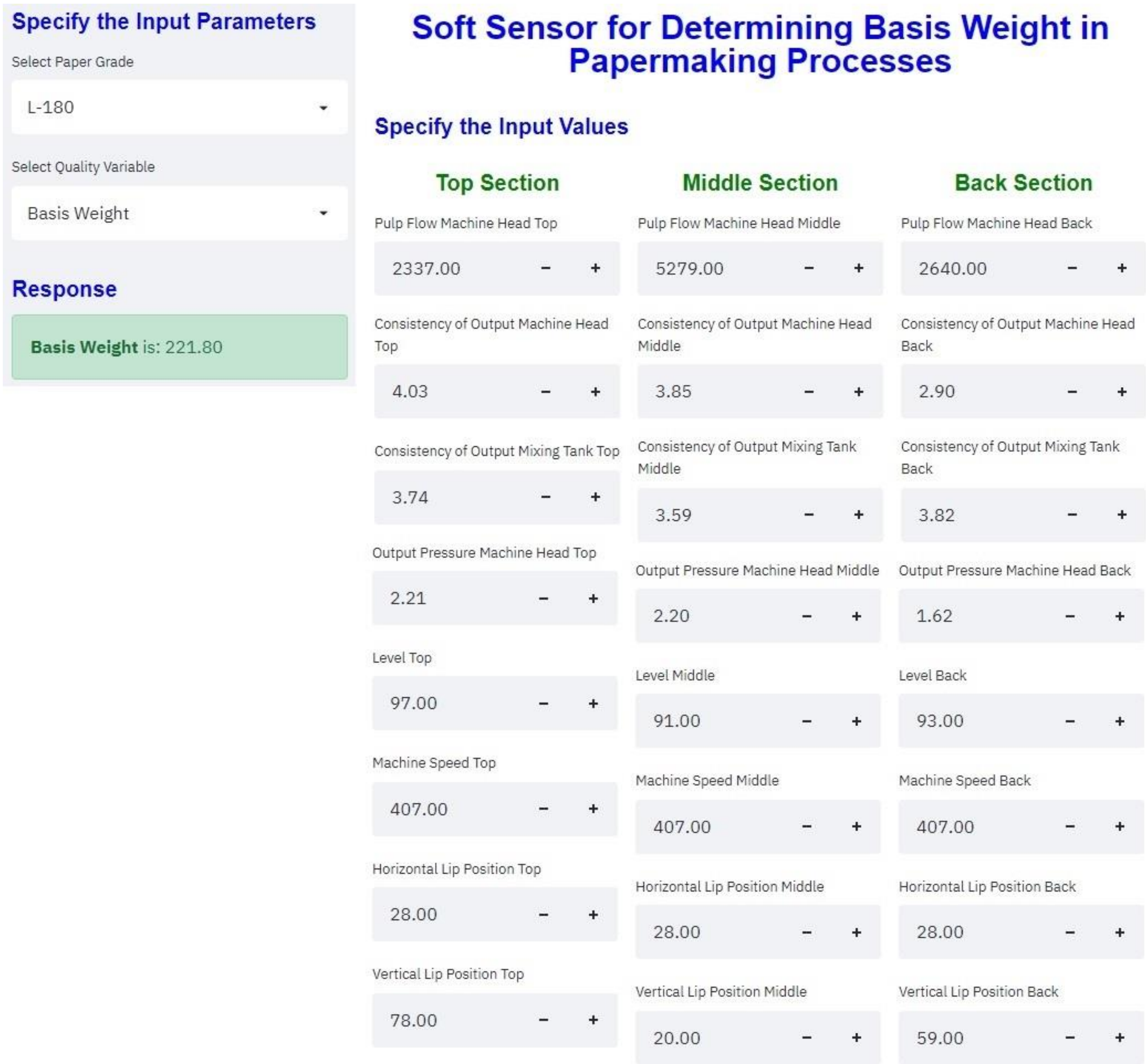


Fig. 4.6 Graphic user interface.

A user interface was developed in Python programming language by using Spyder as development environment. In other hand, Streamlit app library is used to allow the interface to run in a web environment. Firstly, the layout for input and output variables was designed, including their text labels. Therefore, as shown in Fig. 4.6, the user must specify the input values for each machine section, the paper grade and quality variable. With these values, the response (basis weight) is shown. The generated package can be saved in any local host and then run it to use the user interface. Moreover, the developed graphical user interface can work in a web environment; hence, it can be manipulated from any place.

On the other hand, although this GUI presented as a soft sensor can estimate the basis weight with reasonable accuracy, general assumptions must be verified. As described by Fortuna et al., the soft sensors exploit the essential information behind the data to build models with excellent performance and robustness [Fortuna-07]; however, this technology could be susceptible to measurements drift from long-term usage, challenging practical usability [Kim-20]. Therefore, although the based-neural network model deployment presented here showed accuracy and reliability using data not included in the building process, the following considerations described in [Chandra-22] will be required in advance.

- If drift is observed from long-term usage, necessary compensation for the network o response variables must be done.
- To assess the performance of the neural network model, periodical experimental trials with known data has to be carried out and the prediction results to be compared with the earlier performance.
- The neural network model shall be trained with relevant additional process data, which can improve the generalization, robustness as well as the precision and accuracy of predictions.
- Since the neural network model performance relies heavily on the historian data for specific paper grades. If there is a significant change in the paper grades included during the design, rebuilding of the neural network model will be recommended.

4.5. Conclusions

The basis weight of paper is a critical quality characteristic that must be monitored and controlled in papermaking. Currently, in the papermaking process, the basis weight and other important quality characteristics are monitored using traditional control charts [Rodríguez-Álvarez-21a] due to the methods used by the quality control laboratory. In addition, the commercial-quality control system (QCS) available on the market is the other alternative to monitor basis weight.

The present work aimed to propose a new alternative to measure basis weight for any papermaking process. The proposed model is advantageous since its development is based on an artificial neural network using the multilayer perceptron approach. Therefore, it has the advantage of predicting the basis weight with reasonable accuracy (greater than 90%) for new operating conditions or data not included in the training and validation process. For this purpose, the performance of the proposed method was validated by using an external dataset not included in the building process of the model. The results showed a mean absolute error of 12.10 grams/m^2. So, the model can predict the basis weight of paper, mainly for the grades from 180 to 250 grams/m^2, reaching an error from 4.8 to 6.7%. Furthermore, the model will work well as a function of the flows, consistencies, pressures, levels, machine speed, and lip position for the top, middle, and back forming sections of the papermaking machine.

One of the main achievements from this study is that model was embedded in a graphic user interface. The generated package can be saved in any local host and then run it to use the user interface. Moreover, the developed model can work in a web environment. Thus, the process engineers can calculate basis weight offline without waiting for the quality control laboratory results or the readings shown by the quality control systems (QCS). In addition, continuous improvement engineers can use the user interface mainly in the improvement phase for any six-sigma project. Moreover, the user interface can be used to perform non-invasive experimental designs [Rodríguez-Álvarez-21b], which is one of the main advantages of avoiding the costs of any experimentation process.

Although the model predicts the basis weight with acceptable accuracy, determining optimal operating conditions becomes a complicated function due to the number of independent variables. So, in future work, the user interface will be used to conduct experimental designs aimed at finding optimal operating conditions, mainly in complex processes. Even we will try to link the output data provided by the model through the user interface directly to some specialized statistical software.

Since the explained variance score reached by the model was 94%. Trying to improve this value, in future work, by using k-Means firstly to find the clusters (different types of paper grades), the radial basis function (RBF) approach will be used to train and validate a new model.

5. A Non-invasive Method to Evaluate Fuzzy Process Capability Indices via Coupled Applications of ANN and Plackett-Burman DOE

The analysis of process capability against requirements is often an instrument of change. The traditional and fuzzy process capability approaches are the most useful statistical techniques to determining the intrinsic spread of a controlled process for establishing realistic specifications. In the industry, the traditional approach is the most common used instrument to assess the impact of continuous improvement projects. However, these methods being used to evaluate process capability indices could give misleading results because the dataset being employed corresponds to the final product/service measures. This chapter reviews an alternative procedure to evaluate the fuzzy process capability indices, based on the statistical methodology involved in troubleshooting and design of experiments essential in affecting change. Firstly, a model with reasonable accuracy is developed by using a neural network approach. This model is embedded in a graphic user interface (GUI). Using the GUI, an experimental design is carried out, first to know the membership function of the process variability, and after this variability is included in the model, again, an experimental design is carried out to identify the improved process operating conditions by the settings of the significative independent variables. With these being identified better operating conditions and including the minimum error reached for each independent variable, a new dataset is generated. Again, the GUI is used to get a new prediction for the response variable. Finally, using the triangular membership function, and the predicted response values it is determined the fuzzy process capability indices. The feasibility of the proposed method was verified by selecting a random basis weight dataset of the papermaking process. The results indicate that the proposed method gives us a better overview because it displays a range of values instead of a just one. The same as for the fuzzy approach, this method show the true potential of the process performance. The proposed method can be considered non-invasive.

5.1. Introduction

Statistical process control (SPC) is one of the methods most used in manufacturing industries to evaluate, monitor, and to identify change for process improvements. Thus, is key in improving the quality of products and, ensures the statistical process control [Choi-20; Kaya-11a]. The Shewhart control chart is a well-known, powerful method to examine the steadiness of a process. The control chart is a procedure to study a process from a sequence of random samples taken from the process. Data presented in the form of a control chart basis, patterns of runs, presence of outliers in the data, will often suggest areas of opportunity for process improvement. Troubleshooting is successful when provide us information when the trouble began and what may be the cause of it. The process capability is independent of any specification, it represents the natural behavior of the process after the unnatural interferences are eliminated, it is an innate occurrence and is measured by the in-control chart variation. For these purposes, the traditional control technique introduced in 1924 by Walter Shewhart has been widely used in the manufacturing and service industries [Camargo-10; Dudek-Burlikowska-05; Shamsuzzaman-15; Zaman-20; Zhiyuan-15].

Monitoring whether the process is in statistical control has been the primary function of the control charts. They are based on data representing one or several products or service quality characteristics [Kaya-11a]. If these characteristics are measured based on numerical scales; the variable control charts must be used. In other hand, attribute control charts must be used if the quality characteristic cannot be easily represented in numerical form. However, for at least three decades, trends in research have dealt with the issue of control charts based on the fuzzy set theory [Chang-96; Gülbay-06; Cheng-05; Gülbay-07], and at present, this approach is still widely used [Hesamian-18; Kaya-17; Shabani-18; Bazhanov-20; Kaya-20].

Another SPC tool, the process capability analysis, is very well defined as the capacity of a process to meet customer expectations defined as specification limits [Kaya-10a]. Process capability indices are summary statistics that measure the process characteristics overall or potential performance (variables or attributes) relative to the target and specification limits [Kaya-10b]. This approach is helpful to define a relationship between the process capacity and the specification limits. This correspondence is made by forming the width ratio between the specification limits and the natural width tolerance set as six process standard deviations units [Montgomery-20].

The main outputs for any process capability analysis will define whether a process has the capability to produce items with-in the specification limits predetermined by the customer. A larger value of the process capability index implies a high process yield; a lower one implies a low process yield. However, this process only expresses its capability at that instant, and it should never be considered as the capability of the process in the future [Deleryd-98]. The typical process capability indices found in the literature are C_p, C_{pk}, C_{pm}, and C_{pmk} [Kotz-02]. In this research, the C_p and C_{pk} are only analyzed.

The C_p index called in literature as precision index [Kane-86] is defined as the ratio between specifications limits over the process spread (6σ) [Kaya-10a]. The index represents how well the process fits between upper and lower specifications limits, describing the customer product requirements. When the process variation is considerable, the C_p value is small what means a poor process capability. Since this index never considers any process shift, if the process average is not centered near the midpoint of specification width, then the C_p index could give misleading process performance. So, a new process capability index called C_{pk} was introduced by Kane in 1986 [Kane-86]. The main use of the C_{pk} index is to indicate the variability associated with a process. This index is widely used to relate the natural tolerances (3σ) to the customer requirements by considering the location of the process mean. Like to C_p index, a greater value for the C_{pk} index is desired. A C_{pk} index value greater or equal than 1.33 is recommended [Bottani-21]. However, the C_p and C_{pk} indices are not related to the cost of failing to meet the customer's target requirement. On the other hand, the C_{pm} index introduced by Hsiang and Taguchi (1985) measures a process's ability to cluster around the target and reflects the degree of process targeting [Hsiang-85]. However, the information provided by the C_{pm} index could be taken when the C_p and C_{pk} indices values are the same [Montgomery-20].

Because the fuzzy set theory introduced by Zadeh (1965) [Zadeh-65] has demonstrated to deal with imprecise information, its capability to determine flexible parameters and to analyze the results shows more sensitiveness [Kaya-11b]. The fuzzy approach has received attention for the last two decades. Several studies that include the fuzzy set theory to calculate process capability indices can be found in the literature [Kaya-11b; Chen-08; Chen-03; Gao-03; Hsu-08; Kahraman-09a; Kahraman-09b; Kaya-09a; Kaya-09b; Kaya-08; Kaya-09c; Kaya-09d; Kaya-10c; Kaya-11c; Lee-01; Lee-99; Parchami-07; Parchami-10; Parchami-05; Shu-09; Tsai-06; Wu-09; Yongting-96]. Since the introduction of the neutrosophic logic (an extension of fuzzy logic), it also has been used to calculate processes capability indices [Aslam-19; Aslam-21; Rao-19].

It is common to use a dataset collected from quality control laboratories or directly from automated measuring instruments that are part of the process to evaluate process performance. As an alternative, the neural networks-based predictive models could work as a source of data when a reasonable accuracy has been reached. A wide range of this kind of model can be found in the literature with application in different fields of science [Andrés-21; Issa-21; Ly-21; Sang-21; Hoang-21; Lee-21; Antonakoudis-21; Alamir-21; Gouda-21; Maya-21; Basir-21].

Because the desired results for process capability indices are of the "bigger is better" type and considering that the process location and variability are two critical parameters in any process performance analysis. The traditional experimental designs are a powerful tool to overcome this problem. This approach has been widely exploited in different fields of science to define optimal process conditions [Turan-11; Bai-19; Yu-18; Laoun-18; Silva-20; Lafossas-19; Silva-21; Sieira-21]. However, although the traditional design of experiments is very common, for almost two decades, the design of experiments approach has also been applied via couple with neural networks models [Mandal-06; Choudhury-03; Balestrassi-09; Elfghi-16; Hu-19; Reichert-20; Moreira-21; Vieira-21; Heinisch-21; Saidi-21].

This chapter presents a novelty method to evaluate process performance by non-invasive approach to calculate the fuzzy process capability indices. The proposed method uses the significative process variables data records that have influence in the response. The data collected is used to develop an artificial neural network model. This model is now being employed as data source, firstly applying it into the design of experiments approach to identify the optimal conditions for the process performance. Once the optimal variables operating values had been obtained, these new operating conditions are re-introduced to the neural network model to calculate the output measures. Measures that are being used to calculate the fuzzy process capability indices. At present, in the literature, it is not found an integral method like the one presented.

This chapter is organized as follows: Section II briefly reviews the traditional and fuzzy methods to calculate process capability indices. Section III presents the proposed methodology by defining a framework. Meanwhile, Section IV presents a real case application presenting data from a papermaking process to validate the proposed method. Finally, the last section presents the conclusions and recommendations.

5.2. A Review of Fuzzy and Traditional Process Capability Indices

5.2.1 Traditional Process Capability Indices C_p and C_{pk}

The two most widely used standard process capability indices are C_p and C_{pk}. Known as traditional process capability indices, these are determined under the assumption that the process is in statistical control, which means that the variation is due only to random causes. In any process capability analysis using these indices, the response variable values are compared against specific limits, the customer specifications. The comparison is made by forming the width ratio between the specification limits to the width of the natural tolerance measured by six standard deviation units [Montgomery-20].

At the beginning it was called precision index [Kane-86], the C_p was the first process capability index to appear in the literature. This index is defined as the ratio of specifications width (USL-LSL) over the six sigma process spread [19, 21]. This index is calculated by using (5-1).

$$C_p = \frac{Allowable\ Process\ Spread}{Actual\ Process\ Spread} = \frac{USL-LSL}{6\sigma} \quad (5\text{-}1)$$

where USL and LSL are the upper and lower specification limits, respectively, while σ is the standard deviation of the process.

Because C_p focuses on the process dispersion, and this index does not consider the centering of the process [Kaya-10a]. The C_{pk} index is being used to overcome this problem. C_{pk} relates the natural process tolerance (3σ) to the specification limits. It is used to describe how well the process fits within the specification limits by considering the location parameter (mean). This index is calculated by using equations from (5-2) to (5-4) [Montgomery-20; Kotz-02; Kane-86].

$$C_{pk} = \min[C_{pl}, C_{pu}] \quad (5\text{-}2)$$

$$C_{pl} = \frac{(\mu-LSL)}{3\sigma} \quad (5\text{-}3)$$

$$C_{pu} = \frac{(\mu-LSL)}{3\sigma} \quad (5\text{-}4)$$

5.2.2 Fuzzy Process Capability Indices with Triangular Fuzzy Numbers

The fuzzy process capability indices are calculated by using different membership functions to generate the fuzzy numbers. However, this study is based on the fuzzy process capability indices using the triangular fuzzy numbers approach, as described by Kaya and Kahraman in 2010 [Kaya-10b].

When a process capability analysis is based on a fuzzy approach, then a fuzzy estimator for σ^2 is essential. This fuzzy parameter is defined by the confidence interval shown in (5-5).

$$\left[\frac{n\hat{\sigma}^2}{\chi^2_{R,\beta/2}}, \frac{n\hat{\sigma}^2}{\chi^2_{L,\beta/2}}\right] \tag{5-5}$$

where $\chi^2_{R,\beta/2}$ and $\chi^2_{L,\beta/2}$ are the points on the right and left sides of the χ^2 Chi square density function, respectively. Where the probability of exceeding the corresponding limit is $\beta/2$. However, this formula is a biased estimator for the variation (σ^2). The equation (5-6) is defined to calculate an unbiased fuzzy estimator.

$$L(\lambda) = [1-\lambda]\chi^2_{R,0.005} + \lambda n \quad R(\lambda) = [1-\lambda]\chi^2_{L,0.005} + \lambda n \tag{5-6}$$

The unbiased $(1-\beta)100\%$ confidence interval for σ^2 should be calculated from (5-7).

$$\tilde{\hat{\sigma}}_c = \left[\frac{n\hat{\sigma}^2}{L(\lambda)}, \frac{n\hat{\sigma}^2}{R(\lambda)}\right], \quad 0 \le \lambda \le 1 \tag{5-7}$$

If the β parameter is considered as α-cut level, then the fuzzy triangular membership function for σ^2 is obtained from (5-7) and described in (5-8). Therefore, the triangular membership functions can be developed by placing the previous confidence intervals on top of the other.

$$(\hat{\sigma}_c)_\alpha = \left[\frac{n\hat{\sigma}^2}{[1-\alpha]\chi^2_{R,\beta/2}+n\alpha}, \frac{n\hat{\sigma}^2}{[1-\alpha]\chi^2_{L,\beta/2}+n\alpha}\right], \quad 0 \le \alpha \le 1 \tag{5-8}$$

When the fuzzy estimator for σ^2 have been determined, then it is possible to establish specification limits as triangular fuzzy numbers (TFN). Assume that the upper and lower specification limits (USL and LSL) are defined as: $U\tilde{S}L = (u_1, u_2, u_3)$, and $L\tilde{S}L = (l_1, l_2, l_3)$.

By including the α-cuts, then these limits are calculated as shown in (5-9) and (5-10), respectively.

$$U\tilde{S}L_\alpha = [(u_2-u_1)\alpha + u_1, (u_2-u_3)\alpha + u_3] \tag{5-9}$$

$$L\tilde{S}L_\alpha = [(l_2-l_1)\alpha + l_1, (l_2-l_3)\alpha + l_3] \tag{5-10}$$

Now, it is possible to calculate the process capability indices. In order to calculate the fuzzy C_p, (5-11) is used. And to estimate the fuzzy C_{pk}, the equations from (5-12) to (5-14) are being used.

$$\left(\tilde{\tilde{C}}_{pc}\right)_\alpha = \left(\frac{[(u_2-u_1)+(l_3-l_2)]\alpha+(u_1-l_3)}{6*\sqrt{\frac{n\hat{\sigma}^2}{(1-\alpha)\chi^2_{L,\beta/2}+(\alpha n)}}}, \frac{[(u_2-u_3)-(l_2-l_1)]\alpha+(u_3-l_1)}{6*\sqrt{\frac{n\hat{\sigma}^2}{(1-\alpha)\chi^2_{R,\beta/2}+(\alpha n)}}} \right) \tag{5-11}$$

$$\left(\tilde{C}_{puc}\right)_\alpha = \left(\frac{[(u_2-u_1)\alpha+u_1]-\mu}{3*\sqrt{\frac{n\hat{\sigma}^2}{(1-\alpha)\chi^2_{L,\beta/2}+(\alpha n)}}}, \frac{[(u_2-u_3)\alpha+u_3]-\mu}{3*\sqrt{\frac{n\hat{\sigma}^2}{(1-\alpha)\chi^2_{R,\beta/2}+(\alpha n)}}} \right) \tag{5-12}$$

$$\left(\tilde{C}_{plc}\right)_\alpha = \left(\frac{\mu-[(l_2-l_3)\alpha+l_3]}{3*\sqrt{\frac{n\hat{\sigma}^2}{(1-\alpha)\chi^2_{L,\beta/2}+(\alpha n)}}}, \frac{\mu-[(l_2-l_1)\alpha+l_1]}{3*\sqrt{\frac{n\hat{\sigma}^2}{(1-\alpha)\chi^2_{R,\beta/2}+(\alpha n)}}} \right) \tag{5-13}$$

$$\tilde{C}_{pkc} = \min\left\{\tilde{C}_{puc}, \tilde{C}_{plc}\right\} \tag{5-14}$$

5.3. Methodology

This section describes the proposed method to evaluate the fuzzy process capability indices. Since the model and the graphic user interface have been already presented in Chapter 4; then, the validation is being presented only for the experimental designs to the process capability indices steps.

5.3.1 Modeling

For any data-set in a science project it is essential to understand, to know how the data have been collected, stored, transformed, reported, and used [Kotu-19]. Furthermore, understanding the range of factors to consider about manufacturing process data is mainly related to the quality and availability of the data, gaps in the data, or lack of data. Depending on the application, the manufacturing process data are stored in different repositories, including public and commercially available databases and private collections [Szymańska-18].

The larger time-consuming part of the data science process is preparing the dataset to suit a data science task [Kotu-19]. Dataset is rarely structured and available in the form required. Most data science algorithms would require data to be structured in a tabular format with records in the rows and variables in the columns. When the data is presented in any other form, the dataset may need to be transformed into the required structure.

Before conducting an in-depth analysis of the data, to explore the dataset is another essential task. Also known as exploratory data analysis which is probably the most time-demanding task of data preparation. This task provides a set of simple tools to achieve a basic understanding of the data and involves computing descriptive statistics and data visualization [Kotu-19]. This task can expose the structure of the data, the distribution of the values, the presence of outlier values, and highlight relationships whiting the dataset. In addition, some descriptive statistics like mean, median, mode, standard deviation, and range for each independent variable provide an easily readable summary of the key characteristics. Furthermore, the parameters could be used in the data imputation process.

Finally, an in-depth analysis of the data is performed to find a model to predict a variable of interest. A model is the abstract representation of the data and the relationships in each a given dataset.

There are a few hundred data science algorithms in use, derived from statistics, machine learning, pattern recognition, and the body of knowledge related to computer science. Fortunately, there are many viable commercial and open-source data science tools on the market to automate the execution of these learning algorithms.

Classification and regression are commonly predictive techniques used to predict an outcome result based on one or more input variables, as is the case in the present study. However, artificial neural networks have been widely used in many applications [Szymańska-18] due to their potential for predictive purposes.

5.3.2 Graphic User Interface

Currently, most intelligent computing devices use graphic user interfaces to reduce user learning curves and have a better interaction with the process [Kirkpatrick-16].

In any development process of a graphic user interface, the interface and interaction design take up most of the time in software use. Although there are many types of GUI's, typically, this tool is composed of two main categories: the containers that represent the menu and the controls that represent the basic objects of the user interaction [Thomas-21]. A common GUI development approach is presented in [Monte-Mor-11].

In this study, the model deployment is presented in a graphic user interface as an interactive soft sensor shown in Chapter 4. The graphic user interface was developed in Python programing language by using the streamlit app.

5.3.3 Experimental Designs

The main reason for using experimental designs is their ability to provide evidence of causality [Antonakis-10; Cambell-63; Falk-09]. The power of experiments to establish cause and effect relationships is critical to developing knowledge in any field of science [Podsakoff-19]. The literature has referred to experimental designs as the gold standard of scientific research [Antonakis-17; Eden-17; Hauser-17]. Moreover, other studies have noted the importance of experimental designs for testing theoretical concepts, and the way for people to better understand the world [Aronson-85; Colquitt-08; Ilgen-85]. Therefore, the main goal of the experimental designs is to determine the causal relationships between independent and dependent variables.

The proposed method includes the experimental designs as one of the main steps to evaluate the process capability indices. However, the experimental design is carried out as a no-invasive approach [Rodriguez-Alvarez-21b]. Furthermore, the proposed method suggests the use of any of the most common experimental design approaches: screening, factorial, response surface, mixture, and Taguchi. But the approach used will depend on the specific research objective. This study uses a Placket-Burman factorial design.

5.3.4 Generate Dataset

Generally, any process capability analyses are carried out using data from quality control laboratories or the measures taken from the quality control system. Several studies can be found in the literature where traditional and fuzzy approaches are used to calculate process capability indices. However, in the present work, the data are taken using the previously developed interactive soft sensor.

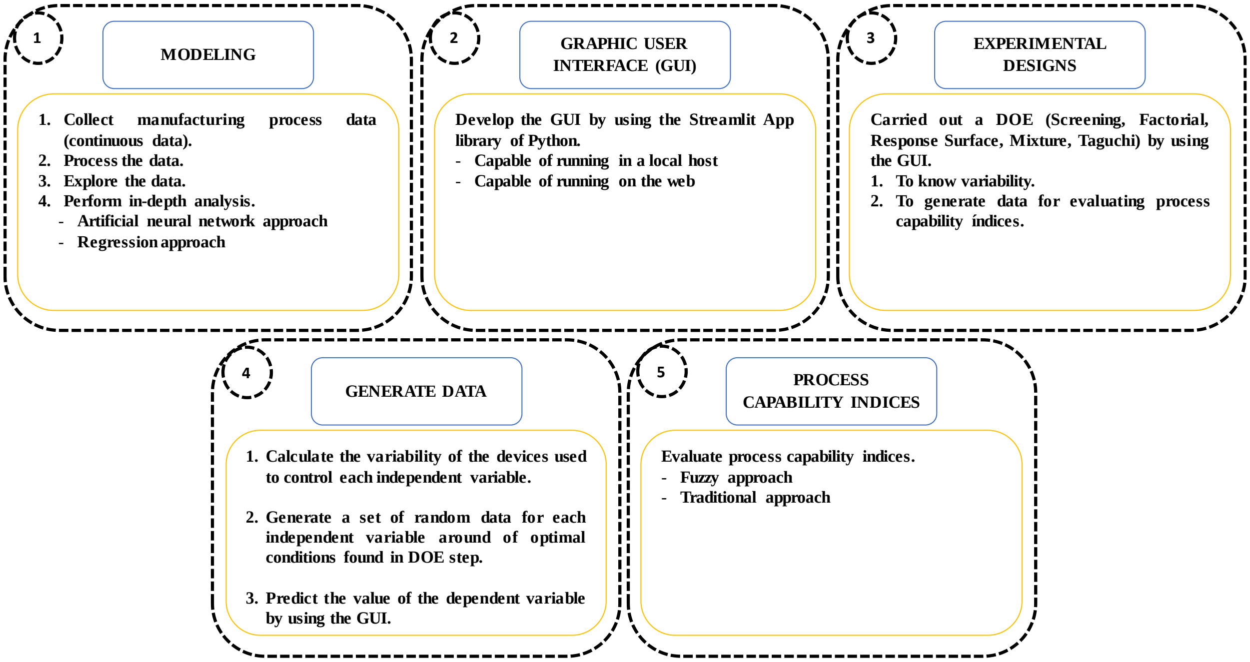


Fig. 5.1 A non-invasive method to evaluate fuzzy process capability indices (Non-I FPCA).

Before generating data for the process capability analysis, the optimal operation conditions determined by the experimental designs step are being considered. However, the values found in the experimental designs are ideal ones. Although, it is complicated to maintain a fixed set point in the process. It is fundamental to determine the variability of the independent variables in the process.

Thus, the variability for all independent variables is firstly determined. This variability is used to generate random data around the set point (optimal condition previously found). The amount of data to be generated is based on cycle time and the process capability to store data.

5.3.5 Process Capability Indices

If the generated data follows a normal distribution, then the process capability indices can be well estimated using the traditional approach. However, as the proposed method uses predicted data, the data will probably show uncertainty. Therefore, the fuzzy process capability analysis is being kept as the better option.

In this study, the Kaya and Kahraman's fuzzy process capability analysis from 2010 is being applied to a papermaking process. In Fig. 5.1 is shown the proposed method called the "non-invasive method to evaluate the fuzzy process capability indices" (Non-I FPCA).

5.4. Real Case Application

The process capability analysis has been held for a papermaking process in a paper grade of 200 grams (L-200). These capability indices have been calculated using a fuzzy environment to get more reliable information about the process capability.

In the modeling process presented in Chapter 4, the used input array size was 182,834 rows by 24 columns, while the output array size was 182,834 rows by one column. For the training and validation process, the used input array size was 164,550 rows by 24 columns, while the output array size was 164,550 rows by one column. In the testing process, the used input array size was 18,284 rows by 24 columns, while the output array size was 18,284 rows by one column.

The resulting mean absolute error was 12.40 grams/m^2. In addition, an external dataset not included in the building process of the model was used to validate the model performance. The resulting mean absolute error was 12.10 grams/m^2 by using the external dataset.

The graphic user interface was developed by using the streamlit library in the Python programming language. So, the model was embedded in the user interface. The generated package can well work in any localhost. Moreover, the model can also work in a web environment, giving to the process engineers the capabilities to calculate basis weight offline. In Chapter 4, the Fig. 4.6 shows the framework of the graphic user interface.

Given the excellent performance showed by the neural network model to predict the basis weight; it was used to evaluate the response in the experimental designs step. In addition, due to the large number of independent variables involved in the papermaking process, the Placket-Burman factorial experimental design was selected. Before carried out the experimental design analysis, all independent variables were coded. Table 5.1 shows the entire list of independent variables and their levels included in the experiment.

Notice that the developed model is deterministic, since under the same operating conditions, the response will always be the same. However, in a real situation, the response must show variability. So, a first experimental design must be carried out to know the variability, and then include it in the model response. Therefore, Minitab-19 was used to generate the fully randomized design table. This table contains one replicate per experiment; so, there are 48 runs

TABLE 5.1. CODES AND LEVELS OF THE INDEPENDENT VARIABLES

Variable Name	Code	Levels	
		Low (-)	High (+)
Pulp Flow at Machine Top	A	1500	2500
Consistency at Machine Top	B	3.5	4.5
Consistency at Tank Top	C	3.5	4.5
Output Pressure at Machine Top	D	1.5	2.5
Level Top	E	85	95
Pulp Flow at Machine Middle	F	4500	5500
Consistency at Machine Middle	G	3.5	4.5
Consistency at Tank Middle	H	3.5	4.5
Output Pressure at Machine Middle	J	1.5	2.5
Level Middle	K	85	95
Pulp Flow at Machine Back	L	2000	3000
Consistency at Machine Back	M	3.5	4.5
Consistency at Tank Back	N	3.5	4.5
Output Pressure at Machine Back	O	1.5	2.5
Level Back	P	85	95
Machine Speed Top	Q	472	473
Machine Speed Middle	R	472	473
Machine Speed Back	S	472	473
Horizontal Lip Position Top	T	25	30
Vertical Lip Position Top	U	75	80
Horizontal Lip Position Middle	V	25	30
Vertical Lip Position Middle	W	15	20
Horizontal Lip Position Back	X	25	30
Vertical Lip Position Back	Y	55	60

without blocks. Each experiment's response (basis weight) was the predicted value by using the neural network model inserted in the graphic user interface.

The results in the Fig. 5.2 shows that the assumptions of the model are met: normality, constant variance, and independence. Meanwhile, Table 5.2 summarizes the analysis of variance. Using the stepwise selection method with an α risk value to enter of 0.15, and an α risk value to

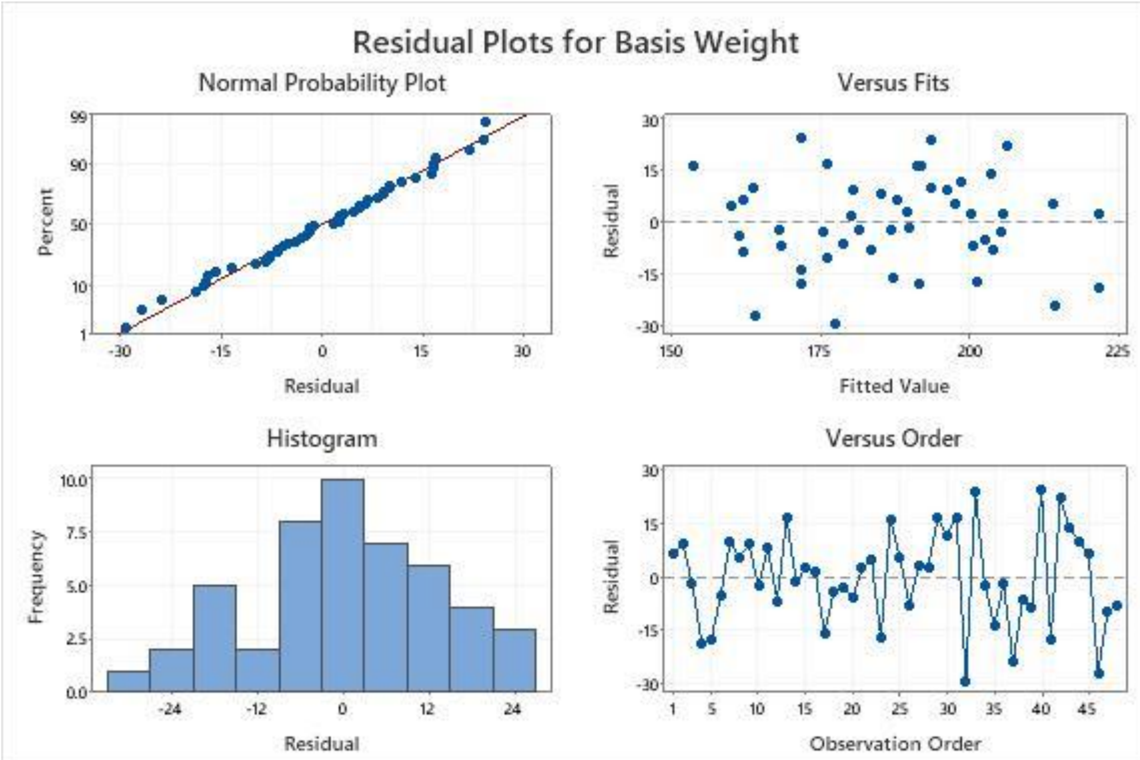


Fig. 5.2 Model assumptions for experimental designs.

TABLE 5.2. ANALYSIS OF VARIANCE

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	8	13777.2	1722.2	8.37	0.000
Linear	8	13777.2	1722.2	8.37	0.000
Pulp Flow at Machine Top	1	851.2	851.2	4.14	0.049
Consistency at Machine Top	1	832.4	832.4	4.04	0.051
Pulp Flow at Machine Middle	1	1730.5	1730.5	8.41	0.006
Level Middle	1	746.8	746.8	3.63	0.064
Pulp Flow at Machine Back	1	890.2	890.2	4.32	0.044
Consistency at Machine Back	1	1199.3	1199.3	5.83	0.021
Horizontal Lip Position	1	733.1	733.1	3.56	0.067
Vertical Lip Position	1	6793.7	6793.7	33.01	0.000
Error	39	8027.4	205.8		
Total	47	21804.7			

remove of 0.15. The results indicate that the process variables, Pulp Flow at Machine Top, Pulp

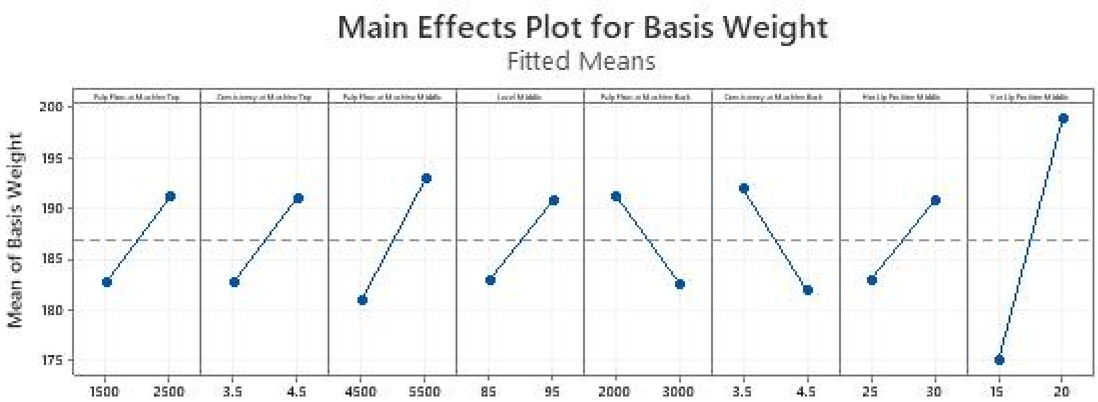


Fig. 5.3 Main effects for the independent variables.

Flow at Machine Middle, Pulp Flow at Machine Back, Consistency at Machine Back, and Vertical Lip Position were significant at a level of 5%. On the other hand, Consistency at Machine Top, Level Middle, and Horizontal Lip Position Middle showed p-values of 0.051, 0.064, and 0.067, respectively. These variables were also considered significant. The main effects plot for each variable mentioned above are shown in Fig. 5.3. Finally, the first optimal operating conditions were determined by using the response optimizer. The results show a desirability index of 1.000 for the optimal values summarized in Table 5.3. Although these variables considerably affect the basis weight, to define the values (in advanced called set point) for the other independent variables is necessary. Therefore, Table 5.3 has also presents the recommended values.

The next step is generating the data to be used to know the expected fuzzy process variability. Thus, the variability for all independent variables is determined. This variability is shown in Table 5.3. By using this variability, a random dataset is generated around the set point for each independent variable. Since, the cycle time of a paper roll is about forty minutes, and because the papermaking process can generate data in time intervals of one minute; hence, a total of forty random data were generated for each independent variable. The resulting array size of 40 rows by 24 columns was introduced in the GUI to predict the basis weight. The predicted values (basis weight) used to calculate the fuzzy process variability are illustrated in Table 5.4. Finally, by using (5-8), the membership function of $\hat{\sigma}_c$ has been calculated and illustrated in Fig. 5.4. The results show that the standard deviation has a range that goes from 1.39 to 4.55. This variability was included in the developed model. So, now the predicted values are affected for any random value taken from this data range.

TABLE 5.3. OPTIMAL VALUES FOR THE INDEPENDENT VARIABLES AND EXPECTED VARIABILITY

Variable	Setting	Expected Variability
Pulp Flow at Machine Top	2500	16.5
Consistency at Machine Top	4.5	0.08
Consistency at Tank Top	4.5	0.08
Output Pressure at Machine Top	1.5	0.08
Level Top	95	0.83
Pulp Flow at Machine Middle	5500	16.5
Consistency at Machine Middle	4.5	0.08
Consistency at Tank Middle	4.5	0.08
Output Pressure at Machine Middle	1.5	0.08
Level Middle	95	0.83
Pulp Flow at Machine Back	2000	16.5
Consistency at Machine Back	3.5	0.08
Consistency at Tank Back	3.5	0.08
Output Pressure at Machine Back	1.5	0.08
Level Back	95	0.83
Machine Speed Top	473	1.65
Machine Speed Middle	473	1.65
Machine Speed Back	473	1.65
Horizontal Lip Position Top	30	0.83
Vertical Lip Position Top	80	0.83
Horizontal Lip Position Middle	25.31	0.83
Vertical Lip Position Middle	15.17	0.83
Horizontal Lip Position Back	30	0.83
Vertical Lip Position Back	60	0.83

Because the developed model is capable to provide different basis weight values for the same provided operating conditions; therefore, it is possible to perform replicated experimental designs, which allow to know the variability, magnitude, and direction of the effects for each independent variable. Thus, by following the same method mention above, Minitab-19 is used

TABLE 5.4. PREDICTED BASIS WEIGHT VALUES (GRAMS) TO ESTIMATE THE VARIABILITY RANGE

n	Basis Weight	*n*	Basis Weight	*n*	Basis Weight	*n*	Basis Weight
1	202.35	11	204.32	21	203.83	31	200.53
2	203.96	12	203.06	22	200.97	32	202.26
3	199.28	13	203.61	23	206.54	33	198.52
4	203.23	14	202.79	24	202.87	34	202.73
5	202.25	15	204.62	25	202.34	35	202.90
6	198.22	16	199.12	26	202.58	36	201.43
7	203.91	17	205.90	27	205.74	37	201.85
8	205.55	18	203.02	28	201.67	38	204.37
9	205.78	19	203.52	29	202.80	39	199.91
10	197.31	20	201.50	30	197.97	40	200.7

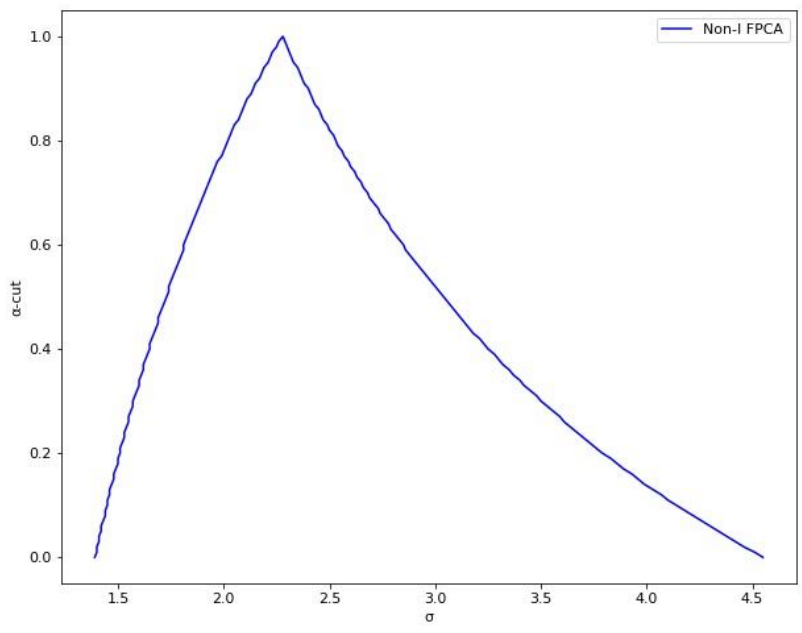


Fig. 5.4 The membership function of $\hat{\sigma}_c$.

again to carried out a replicated experimental design. Firstly, a fully randomized design table is

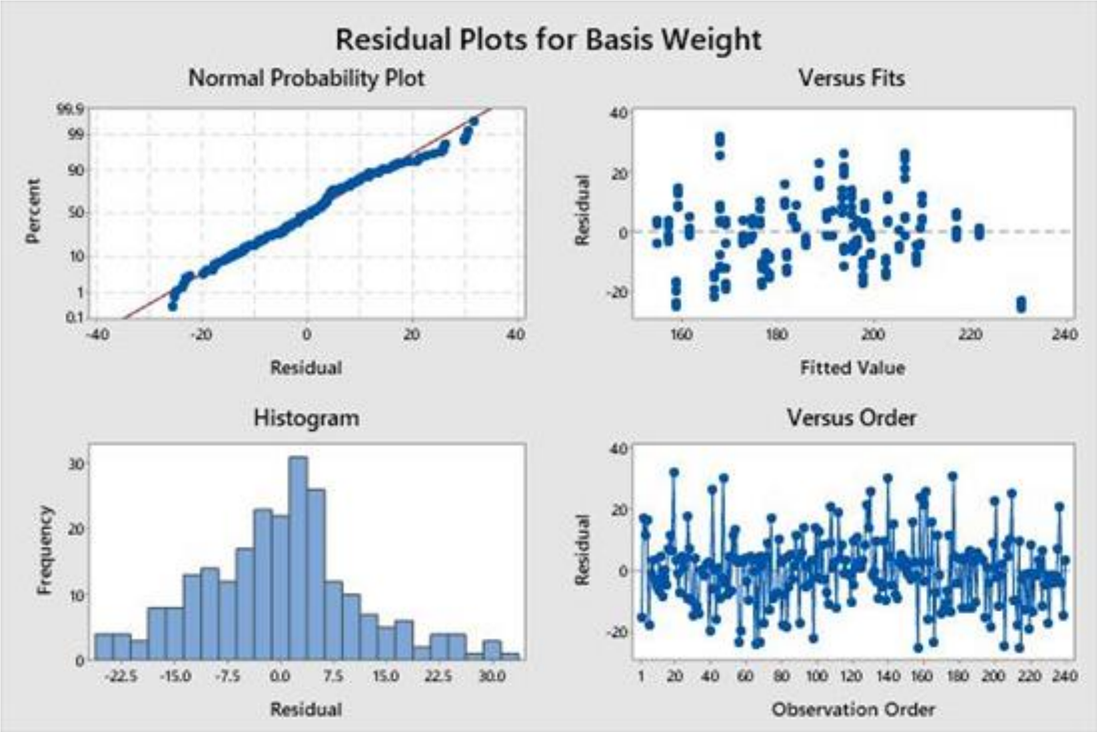


Fig. 5.5 Model assumption for the experimental designs.

generated. This table contains five replicates per experiment; so, there are 240 runs without blocks. The generated matrix size is 240 rows and 24 columns. This matrix is used to estimate the basis weight for each experiment (operating condition).

The results in the Fig. 5.5 shows that the assumptions of the model are again met: normality, constant variance, and independence. Meanwhile, Table 5.5 and Table 5.6 summarizes the coefficients and the analysis of variance respectively. The results indicate that the process variables significant at a level of 5% were: Pulp Flow at Machine Top, Consistency at Machine Top, Pulp Flow at Machine Middle, Output Pressure at Machine Middle, Level Middle, Pulp Flow at Machine Back, Consistency at Machine Back, Consistency at Tank Back, Output Pressure at Machine Back, Level Back, Machine Speed Top, Ver Lip Position Top, Hor Lip Position Middle, and Ver Lip Position Middle. These variables have a significative effect over the basis weight; however, Pulp Flow at Machine Top, Consistency at Machine Top, Pulp Flow at Machine Middle, Level Middle, Consistency at Tank Back, Level Back, Machine Speed Top, Ver Lip Position Top, Hor Lip Position Middle, and Ver Lip Position Middle must be change from low to high level to reduce variability. Meanwhile, the rest of the significative variables must change from high to low. The main effects plot for each variable mentioned above are shown in Fig. 5.6. Finally, the optimal

TABLE 5.5. COEFFICIENTS OF THE MODEL

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF
Constant		186.851	0.770	242.65	0.000	
Pulp Flow at Machine Top	8.068	4.034	0.770	5.24	0.000	1.00
Consistency at Machine Top	8.675	4.337	0.770	5.63	0.000	1.00
Consistency at Tank Top	-1.486	-0.743	0.770	-0.97	0.336	1.00
Output Pressure at Machine Top	2.676	1.338	0.770	1.74	0.084	1.00
Level Top	2.089	1.045	0.770	1.36	0.176	1.00
Pulp Flow at Machine Middle	11.742	5.871	0.770	7.62	0.000	1.00
Consistency at Machine Middle	0.740	0.370	0.770	0.48	0.632	1.00
Consistency at Tank Middle	0.430	0.215	0.770	0.28	0.780	1.00
Output Pressure at Machine Midd	-4.677	-2.338	0.770	-3.04	0.003	1.00
Level Middle	7.840	3.920	0.770	5.09	0.000	1.00
Pulp Flow at Machine Back	-8.951	-4.476	0.770	-5.81	0.000	1.00
Consistency at Machine Back	-10.328	-5.164	0.770	-6.71	0.000	1.00
Consistency at Tank Back	5.727	2.864	0.770	3.72	0.000	1.00
Output Pressure at Machine Back	-5.566	-2.783	0.770	-3.61	0.000	1.00
Level Back	4.611	2.306	0.770	2.99	0.003	1.00
Machine Speed Top	5.248	2.624	0.770	3.41	0.001	1.00
Machine Speed Middle	2.682	1.341	0.770	1.74	0.083	1.00
Machine Speed Back	-2.219	-1.110	0.770	-1.44	0.151	1.00
Hor Lip Position Top	1.176	0.588	0.770	0.76	0.446	1.00
Ver Lip Position Top	3.728	1.864	0.770	2.42	0.016	1.00
Hor Lip Position Middle	7.626	3.813	0.770	4.95	0.000	1.00
Ver Lip Position Middle	23.235	11.617	0.770	15.09	0.000	1.00
Hor Lip Position Back	1.869	0.935	0.770	1.21	0.226	1.00
Ver Lip Position Back	-0.075	-0.038	0.770	-0.05	0.961	1.00

operating conditions were determined by using the response optimizer in Minitab-19. The results show a desirability index of 1.000 for the optimal values summarized in Table 5.7.

The following step is generating the data to carry out now, the fuzzy process capability analysis. Firstly, the variability for all independent variables is determined. The expected

TABLE 5.6. ANALYSIS OF VARIANCE

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	24	78258	3260.8	22.91	0.000
Linear	24	78258	3260.8	22.91	0.000
Pulp Flow at Machine Top	1	3905	3905.1	27.44	0.000
Consistency at Machine Top	1	4515	4515.0	31.73	0.000
Consistency at Tank Top	1	133	132.6	0.93	0.336
Output Pressure at Machine Top	1	430	429.7	3.02	0.084
Level Top	1	262	261.9	1.84	0.176
Pulp Flow at Machine Middle	1	8272	8272.0	58.13	0.000
Consistency at Machine Middle	1	33	32.8	0.23	0.632
Consistency at Tank Middle	1	11	11.1	0.08	0.780
Output Pressure at Machine Midd	1	1312	1312.3	9.22	0.003
Level Middle	1	3688	3687.8	25.91	0.000
Pulp Flow at Machine Back	1	4807	4807.5	33.78	0.000
Consistency at Machine Back	1	6401	6400.6	44.98	0.000
Consistency at Tank Back	1	1968	1968.2	13.83	0.000
Output Pressure at Machine Back	1	1859	1858.8	13.06	0.000
Level Back	1	1276	1275.8	8.96	0.003
Machine Speed Top	1	1653	1652.7	11.61	0.001
Machine Speed Middle	1	431	431.4	3.03	0.083
Machine Speed Back	1	295	295.5	2.08	0.151
Hor Lip Position Top	1	83	83.0	0.58	0.446
Ver Lip Position Top	1	834	833.7	5.86	0.016
Hor Lip Position Middle	1	3489	3489.0	24.52	0.000
Ver Lip Position Middle	1	32392	32391.6	227.61	0.000
Hor Lip Position Back	1	210	209.6	1.47	0.226
Ver Lip Position Back	1	0	0.3	0.00	0.961
Error	215	30598	142.3		
Lack-of-Fit	23	28810	1252.6	134.52	0.000
Pure Error	192	1788	9.3		
Total	239	108856			

variability for each independent variable is shown in Table 5.3. Therefore, by using this variability,

Fig. 5.6 Main effects for the independent variables.

TABLE 5.7. OPTIMAL OPERATING CONDITIONS FOR EACH INDEPENDENT VARIABLE

Variable	Setting	Variable	Setting
Pulp Flow at Machine Top	1500	Consistency at Tank Back	3.5
Consistency at Machine Top	4.5	Output Pressure at Machine Back	2.5
Consistency at Tank Top	4.5	Level Back	85
Output Pressure at Machine Top	1.5	Machine Speed Top	473
Level Top	95	Machine Speed Middle	473
Pulp Flow at Machine Middle	5500	Machine Speed Back	472
Consistency at Machine Middle	3.5	Horizontal Lip Position Top	25
Consistency at Tank Middle	3.5	Vertical Lip Position Top	80
Output Pressure at Machine Middle	2.5	Horizontal Lip Position Middle	25
Level Middle	85	Vertical Lip Position Middle	20
Pulp Flow at Machine Back	2000	Horizontal Lip Position Back	25
Consistency at Machine Back	3.5	Vertical Lip Position Back	60

a new random dataset is generated around the set point defined in Table 5.7. Similarly, to the step

TABLE 5.8. PREDICTED BASIS WEIGHT VALUES (GRAMS) TO ESTIMATE THE FUZZY PROCESS CAPABILITY INDICES

n	Basis Weight	*n*	Basis Weight	*n*	Basis Weight	*n*	Basis Weight
1	204.64	11	206.29	21	206.03	31	200.98
2	209.88	12	203.16	22	204.92	32	198.88
3	204.24	13	198.14	23	197.29	33	208.42
4	198.28	14	201.54	24	205.64	34	200.73
5	205.76	15	203.98	25	205.91	35	209.79
6	204.52	16	212.52	26	200.27	36	204.52
7	200.98	17	210.95	27	203.05	37	205.80
8	199.54	18	207.32	28	200.07	38	197.52
9	201.28	19	197.04	29	206.54	39	204.55
10	202.29	20	206.42	30	199.12	40	201.04

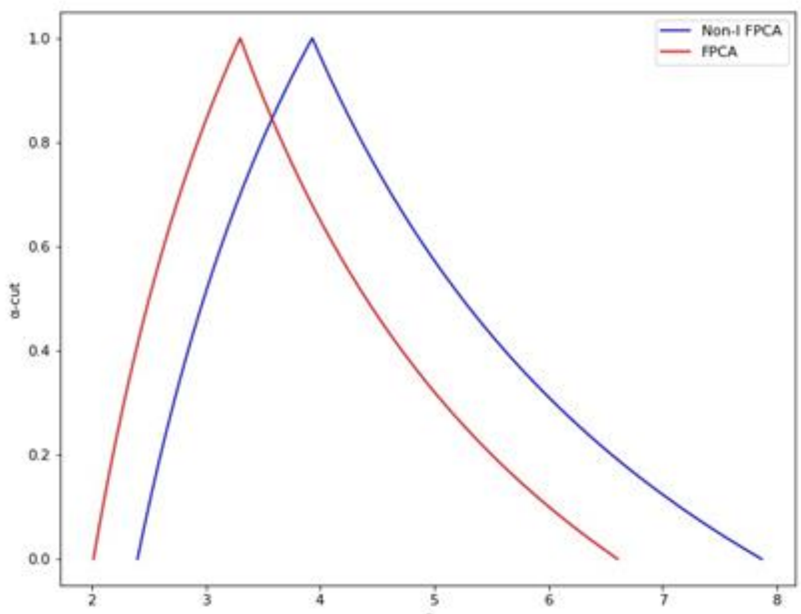


Fig. 5.7 The membership function of $\hat{\sigma}_c$.

where variability range was estimated, the resulting array size was 40 rows by 24 columns. This matrix was introduced in the graphic user interface to predict the basis weight. The predicted values (basis weight) used to apply the fuzzy process capability analysis are illustrated in Table 5.8.

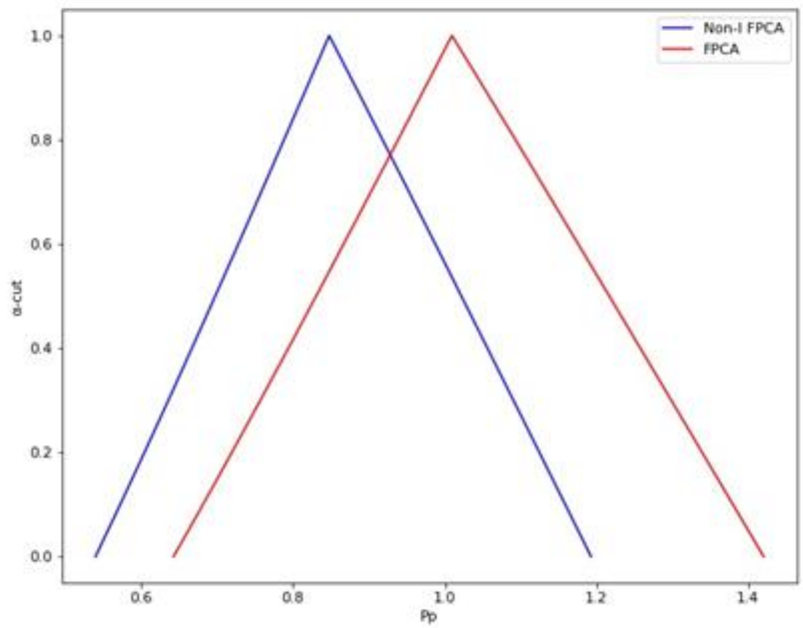


Fig. 5.8 The membership function of $\tilde{\tilde{P}}_{pc}$.

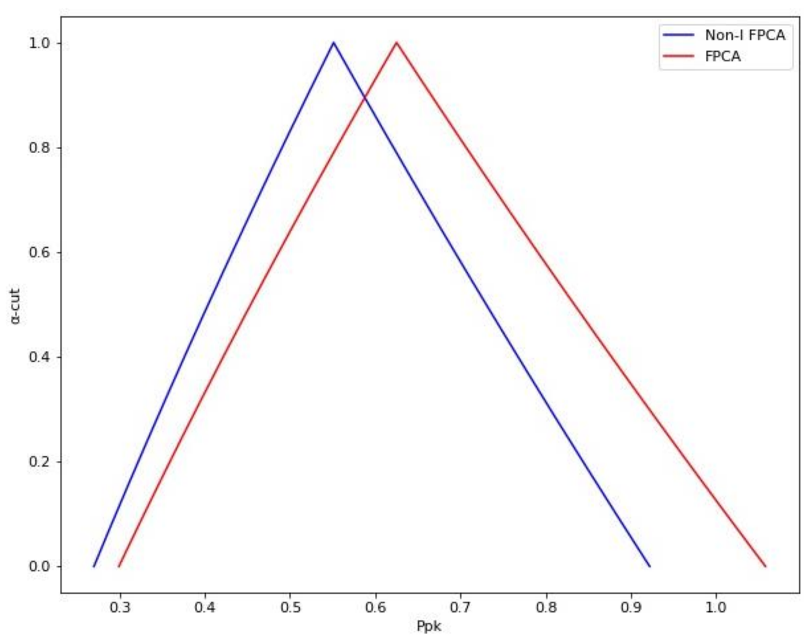


Fig. 5.9 The membership function of $\tilde{P}_{pkc}$.

In the last step of the proposed method, the fuzzy process capability indices are calculated. Firstly, by using (5-8), the membership function of $\hat{\sigma}_c$ has been calculated and illustrated in Fig.

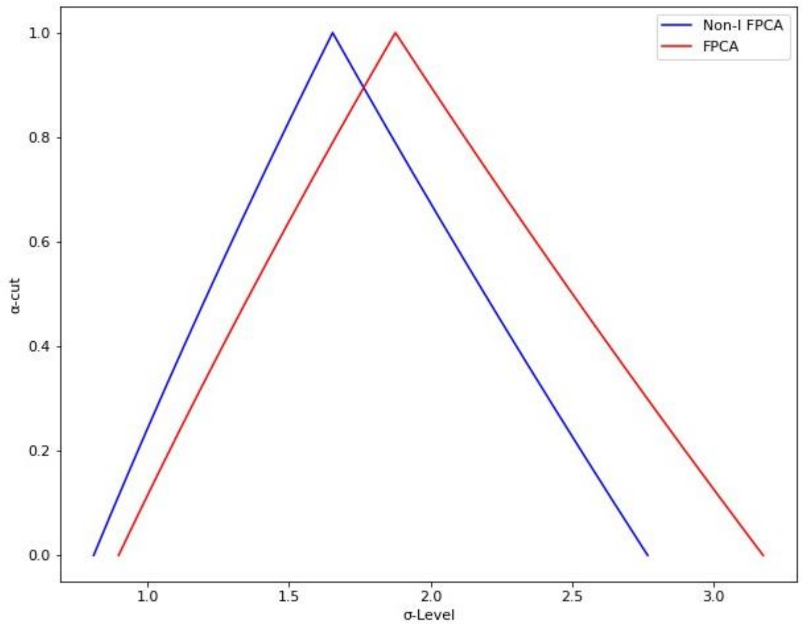


Fig. 5.10 The membership function of σ-level.

5.7. The standard deviation goes from 2.40 to 7.87 for different α-cut values. Notice that this variability is greater than the variability estimated at the beginning. This is because the variability here, includes the variability shown by each and all together independent variables. This variability could be larger; however, by defining the optimal parameters, the variability was reduced in the predicted values of the basis weight. In addition, if the process engineers can have a better control for each of the key significant variables identified in experimental design step; then, the standard deviation would be reduced.

With $\hat{\sigma}_c$ calculated, now it is possible to calculate the fuzzy process capability indices. Because the method used to estimate $\hat{\sigma}_c$ included all data; therefore, $\tilde{\hat{C}}_{pc}$ and $\tilde{C}_{pkc}$ must change by $\tilde{\hat{P}}_{pc}$ and $\tilde{\hat{P}}_{pkc}$. To achieve this aim, the specification limits are defined by using the triangular fuzzy numbers firstly. Since the upper and lower specification limits for a paper grade of 200 grams are 210 and 190 grams, respectively; therefore, the specification limits are defined as follow: $U\tilde{S}L_{\alpha} = TFN(208, 210, 212)$ and $L\tilde{S}L_{\alpha} = TFN(188,190, 192)$.

Now, by using (5-9) and (5-10) the α-cut values for the upper and lower specification limits are obtained as follow: $U\tilde{S}L_{\alpha} = [2\alpha + 208, -2\alpha + 212]$, and $L\tilde{S}L_{\alpha} = [2\alpha + 188, -2\alpha + 192]$. And, by using (5-11), the membership function of $\tilde{\hat{P}}_{pc}$ is calculated and depicted in Fig. 5.8. The

TABLE 5.9. BASIS WEIGHT VALUES (GRAMS) FROM QCS

n	Basis Weight	n	Basis Weight	n	Basis Weight	n	Basis Weight
1	203.67	11	209.57	21	202.09	31	206.58
2	201.22	12	209.87	22	204.23	32	205.35
3	200.31	13	206.35	23	204.23	33	204.30
4	199.81	14	203.81	24	205.47	34	203.06
5	200.24	15	201.13	25	208.67	35	202.57
6	200.97	16	199.70	26	209.43	36	202.33
7	201.80	17	198.41	27	208.91	37	202.06
8	203.30	18	198.24	28	208.36	38	202.50
9	205.18	19	199.10	29	207.88	39	203.12
10	207.08	20	200.15	30	207.29	40	203.93

range for $\tilde{\tilde{P}}_{pc}$ goes from 0.54 to 1.19 with different α-cut values.

The equations (5-12) and (5-13) are used to calculate the memberships functions of $\tilde{P}_{puc}$ and $\tilde{P}_{plc}$. $\tilde{P}_{puc}$ change between 0.27 to 0.92 with different α-cut values. Meanwhile, $\tilde{P}_{plc}$ change between 0.69 to 1.68 with different α-cut values. Therefore, by using (5-14), the range for $\tilde{P}_{pkc}$ goes from 0.27 to 0.92, as shown in Fig. 5.9.

The membership functions of σ-level were also calculated using the following equation: $\sigma = 3 * \tilde{P}_{pkc}$. The σ-level change between 0.81 to 2.77, as shown in Fig. 5.10.

Finally, a dataset of 200 grams' paper grade randomly selected from the quality control system is collected to compare the proposed method against the traditional and fuzzy approaches. For this purpose, forty continued basis weight readings between 190 to 210 grams were taken. And then, by using the traditional process capability analysis, the P_p and P_{pk} indices were calculated. The used dataset is illustrated in Table 5.9. The analysis was carried out in Minitab-19. The results show a P_p of 1.01 and a P_{pk} of 0.63 as shown in Fig. 5.11. In addition, by using the same dataset, the fuzzy process capability indices were calculated for different α-cut values. The results show that the standard deviation goes from 2.02 to 6.61. The P_{pc} ranges go from 0.64 to 1.42, while the $\tilde{P}_{pkc}$ goes from 0.30 to 1.06. Finally, the σ-level changes between 0.90 to 3.17. These values are presented from Fig. 5.7 to Fig. 5.10, respectively.

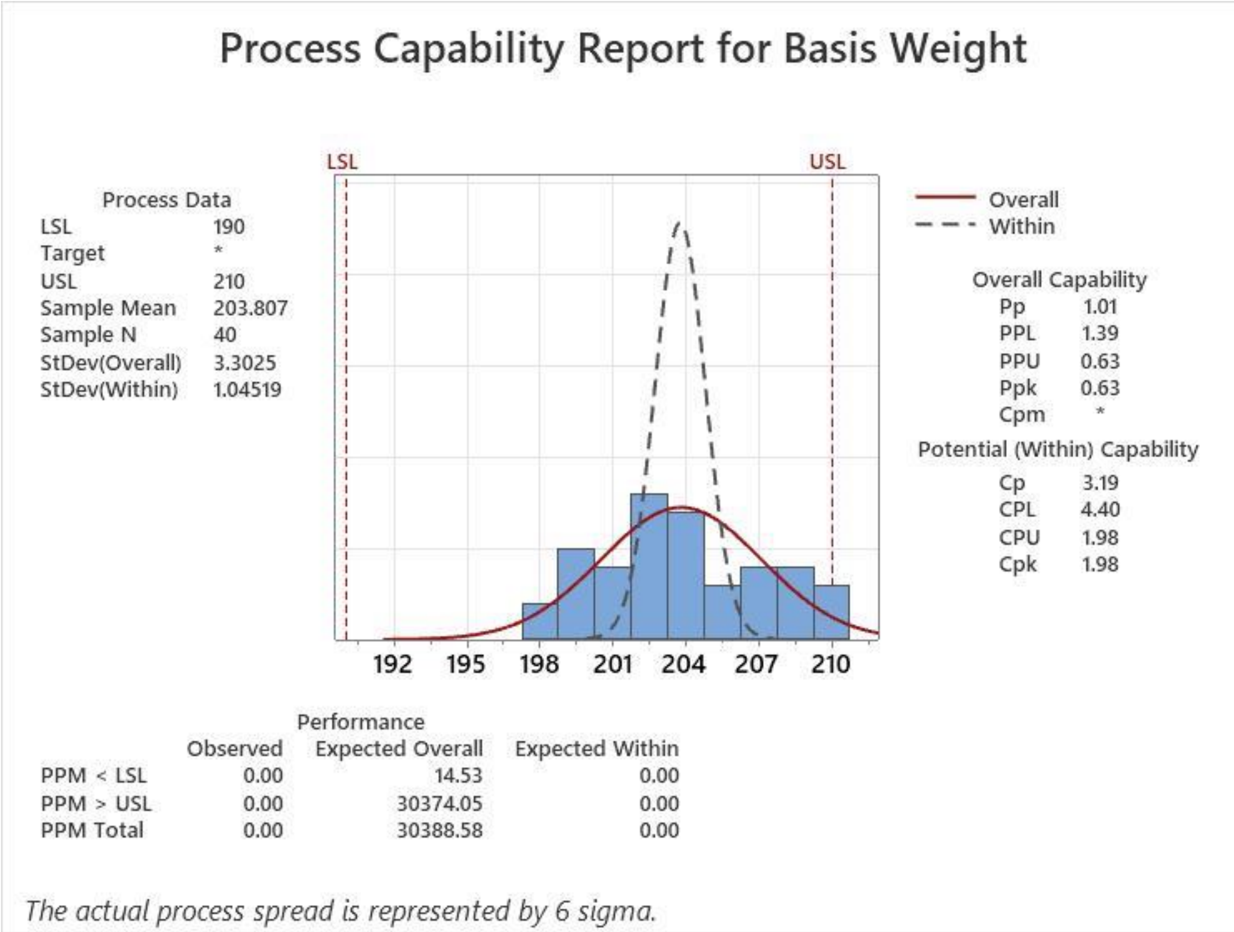


Fig. 5.11 Traditional process capability indices.

5.5. Conclusions

Unlike to the existing methods, the proposed method does no uses measures of the final product/service. Instead of this, the used dataset corresponds to predicted values made by the trained model. Therefore, the fuzzy process capability indices are determined by using data directly from each independent variable that affects the response, including its variability.

In the traditional approach to evaluate process capability indices, the values of the response variable are usually close to the target value, because the data come from normal process. In the proposed method, the experimental designs were used first to know the membership function of the process variability. This variability was included in the model to carry out a replicated experimental design to define the optimal operating conditions that will bring the response variable closer to a target value.

The P_p and P_{pk} capability indices estimated using the traditional approach are within the range of values calculated with the proposed method for this same indices. In other hand, when the minimum and maximum values are calculated with the proposed and existing fuzzy methods, the indices with the proposed method will always be larger than the existing fuzzy methods. In addition, since most of the processes tend to maintain or even decrease their performance, and because the variability of the independent variables was included; therefore, the results indicate that the proposed method gives us a better overview than the traditional and fuzzy approaches related to the true potential of the process performance. The observed advantages of the proposed method come from focusing on to find the optimal operating conditions of the process parameters to obtain the desired result of the paper weight and reducing its variability.

An important benefit of using the proposed method is that it allows us to know the impact on performance and variability of the significant variables of the paper manufacturing process; thus, this information should guide us in the product and process improvements.

Furthermore, this method is helpful for slow processes where cycles times are very long and when collecting enough data to perform a process capability analysis is complicated. In addition, if data can be collected for each process variable; then, the process capability indices can be calculated for each manufactured product/service.

On the other hand, since a variability factor is added around an optimal value defined in the experimental design process, the proposed method's performance evaluation results will always present a different value even when using the same data collected for each independent variable. Therefore, this disadvantage will affect the variation of the intersection point probability concerning the fuzzy approach presented in [Kaya-10b].

Because the fuzzy process capability indices were estimated using the triangular membership function, in future research, the proposed method will use other fuzzy membership function to compare their results with the reality.

General Conclusions

In this doctoral dissertation, the statistical thinking approach has been presented as an alternative management practice to the process control using individual measurements control charts, and to measure processes performance using the P_p and P_{pk} capability indices. Both proposals are focused on complex processes, in which it is difficult to collect sufficient data on quality variables, in addition to the presence of uncertainty in the measurements. Furthermore, to overcome the uncertainty problem, both proposals were developed under a fuzzy environment.

In Chapter 1 was presented an overview of the statistical thinking approach as an alternative management practice to reduce process variability, and as consequence to improve the process capability indices P_p and P_{pk}. In addition, a general review of the pulp and paper industry was presented in which the validations of the proposals described in this dissertation were carry out.

In Chapter 2 a first implementation of modeling + experimental designs approach has been presented to the parameters optimization. Taking advantage of the large amount of available data in the papermaking process, in a first stage, two models were trained: linear regression and regression tree. The results showed that the regression tree model had a better predictive capacity than linear regression. Hence, this model was used as source of output variable measurement to carry out the full factorial experimental design. Using this approach, four independent variables were significant at 5% alpha level. Therefore, the optimal parameters were defined. Since non-invasive experiments reduces the risk of off quality and downtime, one of the most significant findings from this study is that the proposed approach: modeling in addition to designed experiments could be implemented to other complex process sections.

In Chapter 3 was presented the proposal of the fuzzy individual and moving range control charts, which were based on the α-cut fuzzy midrange approach given in [Kaya-17]. The proposed method in this dissertation to generate fuzzy numbers is very useful, because it is based on the sigma level of the process and the observed variation in each sample. Thus, it can be adapted to any type of process. One of the most significant findings from this proposal is that the fuzzy individual and moving range control charts are more flexible, because the amplitude between the upper and lower control limits is greater than those shown by the traditional individual control charts. Therefore, by increasing the amplitude, then false alarms could be prevented due to the uncertainty coming from the measurement system or the nature of the process.

In Chapter 4 was presented an alternative method to determine the basis weight for any papermaking process based in an artificial neural network model. The predictive model was inserted in a graphic user interface (GUI), which can run in a web environment. The model had the advantage of predicting the basis weight with reasonable accuracy with a mean absolute error of 12.40 grams/m^2. The model performance was validated by using an external real dataset not included in the building process. The findings showed a mean absolute error of 12.10 grams/m^2. Notice, the model can predict the basis weight of paper, mainly for the grades from 180 to 150 grams/m^2, reaching an error from 4.8 to 6.7%.

Finally, in Chapter 5 was presented the proposal to estimate the process capability indices under a fuzzy approach. Modeling + experimental design was presented as a non-invasive approach. This is essential, first to know the process variability, and second to reduce variability in the quality control variable. Unlike to the existing methods, the proposal in this dissertation does not uses measures of the final product/service. Instead of this, the used dataset corresponds to predicted values made by the model, trained in the previous chapter. In addition, the fuzzy process capability indices are determined by using data directly from each independent variable that affects the response, including its variability. The proposal performance was validated using a real basis weight dataset. The findings showed that the process capability indices P_p and P_{pk} estimated with the proposal in this dissertation are closer to the process reality than the existing traditional and fuzzy methods.

In this doctoral thesis, firstly, it is presented the control charts for individual data based on a fuzzy approach, which show greater flexibility (greater amplitude between upper and lower control limits) than traditional control charts. This flexibility is achieved due to the inclusion of the variation when generating the fuzzy number with a triangular membership function. In addition, the process capability indices based on a fuzzy approach were presented, following the triangular membership function. However, unlike the current methods, the indices presented in this thesis are calculated with data provided by a predictive model. This model includes the variation of each process variable. Therefore, using the proposed method, it is not necessary to invade the process. Furthermore, by including the variation, the indices will be closer to the process reality.

As future work, the performance of the fuzzy individual and moving range control charts could be investigated using the trapezoidal fuzzy membership function. Furthermore, this membership function could also be used to evaluate the performance of the non-invasive fuzzy process capability indices.

Conclusiones Generales

En esta tesis doctoral se ha presentado el enfoque del pensamiento estadístico como una práctica de gestión alternativa al control de procesos mediante gráficos de control de medidas individuales, y a la medición del rendimiento de los procesos mediante los índices de capacidad P_p y P_{pk}. Ambas propuestas se enfocan en procesos complejos, en los que es difícil recoger suficientes datos sobre las variables de calidad, además de la presencia de incertidumbre en las mediciones. Para superar el problema de la incertidumbre, ambas propuestas se desarrollaron bajo un entorno difuso.

En el Capítulo 1, se presentó una visión general del enfoque del pensamiento estadístico como una práctica de gestión alternativa para reducir la variabilidad del proceso, y como consecuencia para mejorar los índices de capacidad del proceso P_p y P_{pk}. Además, se presentó una revisión general de la industria de la celulosa y el papel en la que se llevaron a cabo las validaciones de las propuestas descritas en esta disertación.

En el Capítulo 2, se ha presentado una primera aplicación del enfoque de modelado + diseños experimentales para la optimización de parámetros. Tomando ventaja de la gran cantidad de datos disponibles en el proceso de fabricación de papel, en una primera etapa se entrenaron dos modelos de: regresión lineal y árbol de regresión. Los resultados mostraron que el modelo de árbol de regresión tuvo una mejor capacidad de predicción que el modelo de regresión lineal. Por lo tanto, este modelo se utilizó como fuente de medición de la variable de salida para llevar a cabo el diseño experimental factorial completo. Utilizando este enfoque, cuatro variables independientes resultaron significativas a un nivel alfa del 5%. Por lo tanto, se definieron los parámetros óptimos. Dado que los experimentos no invasivos reducen el riesgo de pérdida de calidad y el tiempo de inactividad, uno de los hallazgos más significativos de este estudio es que el enfoque propuesto: el modelado, además de los experimentos diseñados, podría aplicarse a otras secciones de procesos complejos.

En el Capítulo 3, se presentó la propuesta de los gráficos de control difuso individual y de rango móvil, los cuales se basaron en el enfoque de rango medio difuso α-cut presentado en [Kaya-17]. El método propuesto en esta tesis para generar números difusos es muy útil, porque se basa en el nivel sigma del proceso y en la variación observada en cada muestra. Por lo tanto, se puede adaptar a cualquier tipo de proceso. Uno de los hallazgos más significativos de esta propuesta es que los gráficos de control difuso individual y de rango móvil son más flexibles, porque la amplitud entre los límites de control superior e inferior es mayor que la que muestran los gráficos de control individual tradicionales. Por lo tanto, al aumentar la amplitud, se podrían evitar las falsas alarmas debidas a la incertidumbre procedente del sistema de medición o de la naturaleza del proceso.

En el Capítulo 4, se presentó un método alternativo para determinar el peso base de cualquier proceso de fabricación de papel basado en un modelo de red neuronal artificial. El modelo predictivo se insertó en una interfaz gráfica de usuario (GUI), que puede ejecutarse en un entorno web. El modelo tuvo la ventaja de predecir el peso base con una precisión razonable, con un error absoluto medio de 12.40 gramos/m^2. El desempeño del modelo se validó utilizando un conjunto de datos reales externos no incluidos en el proceso de desarrollo del modelo. Los resultados mostraron un error absoluto medio de 12.10 gramos/m^2. Se observó que el modelo puede predecir el peso base del papel, principalmente para las calidades de 180 a 150 gramos/m^2, alcanzando un error de 4.8 a 6.7%.

Finalmente, en el Capítulo 5 se presentó la propuesta para estimar los índices de capacidad del proceso bajo un enfoque difuso. Se presentó el modelado + diseño experimental como un enfoque no invasivo. Esto es esencial, primero para conocer la variabilidad del proceso, y segundo para reducir la variabilidad en la variable de control de calidad. A diferencia de los métodos existentes, la propuesta de esta tesis no utiliza medidas del producto/servicio final. En su lugar, el conjunto de datos utilizado corresponde a los valores predichos por el modelo, entrenado en el capítulo anterior. Además, los índices de capacidad del proceso difuso se determinan utilizando directamente los datos de cada variable independiente que afecta a la respuesta, incluyendo su variabilidad. El rendimiento de la propuesta se validó utilizando un conjunto de datos de peso base real. Los resultados mostraron que los índices de capacidad del proceso P_p y P_{pk} estimados con la propuesta de esta tesis, se acercan más a la realidad del proceso que los métodos tradicionales y difusos existentes.

En esta tesis doctoral se presentó primero, los gráficos de control para datos individuales basados en un enfoque difuso, los cuales muestran mayor flexibilidad (mayor amplitud entre los límites de control superior e inferior) que los gráficos de control tradicionales. Esta flexibilidad se alcanza debido a la inclusión de la variación cuando se genera el número difuso perteneciente a una función triangular. Adicionalmente, se presentaron los índices de capacidad de proceso basados también en un enfoque difuso, siguiendo la función de pertenencia triangular. Sin embargo, a diferencia de los métodos actuales, los índices presentados en esta tesis, se calculan con los datos proporcionados por un modelo predictivo, el cual incluye la variación de cada variable de proceso. Por tanto, mediante el uso del método propuesto no es necesario invadir el proceso y la inclusión de la variación permite tener índices más cercanos a la realidad del proceso.

Como trabajo futuro, se podría investigar el rendimiento de los gráficos de control difuso individual y de rango móvil utilizando la función de pertenencia difusa trapezoidal. Además, esta función de pertenencia también podría utilizarse para evaluar el rendimiento de los índices de capacidad de proceso difusos no invasivos.

Appendix

A. LIST OF INTERNAL RESEARCH REPORTS

1) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "Optimization as an epistemological reflection," Internal Report *PhDEngScITESO-17-55-R*, ITESO, Tlaquepaque, México, Dec. 2017.
2) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "Optimization of operating parameters in the rodsizer-spooner section of a paper manufacturing machine using a multiple linear regression model," Internal Report *PhDEngScITESO-18-51-R*, ITESO, Tlaquepaque, México, Dec. 2018.
3) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "Forecasting nile tilapia weight production units in temperate zones using an anfis and linear regression models," Internal Report *PhDEngScITESO-19-12-R*, ITESO, Tlaquepaque, México, Aug. 2019.
4) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "A statistical thinking approach to improve the pulp and paper industry performance index that include environmental contamination," Internal Report *PhDEngScITESO-19-35-R*, ITESO, Tlaquepaque, México, Dec. 2019.
5) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "Analysis and control of the papermaking processes by using fuzzy and traditional individual control charts," Internal Report *PhDEngScITESO-20-09-R*, ITESO, Tlaquepaque, México, May. 2020.
6) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "Fuzzy and Traditional Individual Control Charts for Monitoring Quality in Papermaking by Using an Excel Tool and Streamlit App," Internal Report *PhDEngScITESO-21-11-R*, ITESO, Tlaquepaque, México, Oct. 2021.
7) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "Interactive Soft Sensor Based in an Artificial Neural Network Model for Determining Basis Weight in Papermaking," Internal Report *PhDEngScITESO-21-12-R*, ITESO, Tlaquepaque, México, Oct. 2021.
8) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "A Non-Invasive Method to Evaluate Fuzzy Process Capability Indices via Coupled

Applications of Artificial Neural Networks and Plackett-Burman DoE," Internal Report *PhDEngScITESO-21-14-R*, ITESO, Tlaquepaque, México, Oct. 2021.

9) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, "Parameters Optimization in Papermaking Processes by Using Regression Trees and Full Factorial Design," Internal Report *PhDEngScITESO-21-15-R*, ITESO, Tlaquepaque, México, Oct. 2021.

B. LIST OF PUBLICATIONS

B.1 Journals Papers

1) J. L. Rodríguez-Álvarez, R. López-Herrera, I. E. Villalón-Turrubiates, G. Grijalva-Ávila, A. Soto-Cabral, "Forecasting nile tilapia weight production units in temperate zones using an anfis and linear regression models," *J Aquacult Eng Fish Res*, vol. 5, no. 1, pp. 12-21, 2019. (e-ISSN: 2149-0236; published online: 24 Jun. 2019).
2) Rodríguez-Álvarez, J. L., López-Herrera, R., Villalón-Turrubiates, I. E., Grijalva-Avila, G., & García-Alcaraz, J. L., "Modeling and parameter optimization of the papermaking processes by using regression tree model and full factorial design," *TAPPI JOURNAL*, vol. 20, no. 2, 2021, pp. 123-137. (ISSN: 0734-1415; doi: 10.32964/TJ20.2.123).
3) José L. Rodríguez-Álvarez, Rogelio López-Herrera, Iván E. Villalón-Turrubiates, Rey D. Molina-Arredondo, Jorge L. García-Alcaraz, Óscar D. Hernández-Olvera, "Analysis and control of the paper moisture content variability by using fuzzy and traditional individual control charts," *Chemometrics and Intelligent Laboratory Systems*, vol. 208, 2021. (ISSN: 0169-7439; doi: 10.1016/j.chemolab.2020.104211).

C. MOISTURE CONTENT DATA OF THE LC-240 COATED PAPER

Date	Shift	Time	Roll #	Measure	Date	Shift	Time	Roll #	Measure
08-jun-19	1	11:40	4657	5.0	10-jun-19	3	03:07	4727	4.6
08-jun-19	1	12:10	4658	5.1	10-jun-19	3	03:49	4728	5.5
08-jun-19	1	12:35	4659	5.1	10-jun-19	3	04:34	4729	5.5
08-jun-19	1	13:15	4660	5.1	10-jun-19	3	05:17	4730	5.1
08-jun-19	2	14:00	4661	5.2	11-jun-19	1	07:10	4731	4.1
08-jun-19	2	14:40	4662	5.0	11-jun-19	1	12:05	4734	4.3
08-jun-19	2	15:15	4663	5.0	11-jun-19	2	18:27	4740	4.7
08-jun-19	2	15:45	4664	4.5	11-jun-19	2	19:14	4741	5.0
08-jun-19	2	16:55	4665	4.1	11-jun-19	2	21:49	4742	4.6
08-jun-19	2	18:21	4666	4.5	11-jun-19	3	23:00	4743	4.8
08-jun-19	2	19:03	4667	4.6	11-jun-19	3	23:43	4744	4.8
08-jun-19	2	19:46	4668	4.6	11-jun-19	3	01:40	4745	4.8
08-jun-19	2	20:28	4669	4.6	11-jun-19	3	02:35	4746	4.8
08-jun-19	2	21:11	4670	4.6	12-jun-19	2	15:50	4763	4.6
08-jun-19	2	21:52	4671	4.6	12-jun-19	2	17:00	4764	4.6
08-jun-19	3	22:36	4672	4.9	12-jun-19	2	18:02	4765	4.5
08-jun-19	3	23:16	4673	5.0	12-jun-19	2	18:44	4766	5.3
08-jun-19	3	00:37	4674	4.6	12-jun-19	2	19:24	4767	5.4
08-jun-19	3	01:22	4675	4.6	12-jun-19	2	21:51	4768	4.9
08-jun-19	3	02:04	4676	4.6	12-jun-19	3	22:31	4769	5.0
08-jun-19	3	02:30	4677	4.6	12-jun-19	3	23:11	4770	5.3
08-jun-19	3	03:37	4678	4.5	12-jun-19	3	23:58	4771	5.3
08-jun-19	3	04:52	4679	4.6	12-jun-19	3	00:40	4772	5.2
09-jun-19	1	06:00	4680	4.3	12-jun-19	3	01:54	4773	5.3
09-jun-19	1	06:50	4681	4.2	12-jun-19	3	02:35	4774	5.3
09-jun-19	1	07:40	4682	4.2	12-jun-19	3	03:21	4775	5.2
10-jun-19	2	15:55	4725	4.6	12-jun-19	3	04:54	4776	5.3
10-jun-19	3	02:12	4726	4.5	12-jun-19	3	05:36	4777	5.1

D. CONTROL SITUATION IN LC-240 PAPER MOISTURE CONTENT FOR FICC

Roll #	Fuzzy Midrange Value (X)	Status	Roll #	Fuzzy Midrange Value (X)	Status
4657	5.000	In Control	4727	4.617	In Control
4658	5.067	In Control	4728	5.450	Out of Control
4659	5.093	In Control	4729	5.467	Out of Control
4660	5.125	In Control	4730	5.058	In Control
4661	5.150	In Control	4731	4.108	Out of Control
4662	4.992	In Control	4734	4.317	In Control
4663	4.950	In Control	4740	4.674	In Control
4664	4.525	In Control	4741	4.975	In Control
4665	4.092	Out of Control	4742	4.589	In Control
4666	4.526	In Control	4743	4.767	In Control
4667	4.567	In Control	4744	4.750	In Control
4668	4.563	In Control	4745	4.800	In Control
4669	4.600	In Control	4746	4.817	In Control
4670	4.617	In Control	4763	4.558	In Control
4671	4.583	In Control	4764	4.558	In Control
4672	4.908	In Control	4765	4.533	In Control
4673	4.959	In Control	4766	5.343	In Control
4674	4.583	In Control	4767	5.417	Out of Control
4675	4.562	In Control	4768	4.886	In Control
4676	4.575	In Control	4769	5.033	In Control
4677	4.550	In Control	4770	5.317	In Control
4678	4.492	In Control	4771	5.258	In Control
4679	4.583	In Control	4772	5.208	In Control
4680	4.258	In Control	4773	5.333	In Control
4681	4.225	Out of Control	4774	5.267	In Control
4682	4.192	Out of Control	4775	5.201	In Control
4725	4.592	In Control	4776	5.258	In Control
4726	4.539	In Control	4777	5.142	In Control

E. CONTROL SITUATION IN LC-240 PAPER MOISTURE CONTENT FOR FMRCC

Roll #	Fuzzy Midrange Value (*MR*)	Status	Roll #	Fuzzy Midrange Value (*MR*)	Status
4657		In Control	4727	0.135	In Control
4658	0.067	In Control	4728	0.834	Out of Control
4659	0.044	In Control	4729	0.034	In Control
4660	0.077	In Control	4730	0.408	In Control
4661	0.025	In Control	4731	0.950	Out of Control
4662	0.239	In Control	4734	0.208	In Control
4663	0.211	In Control	4740	0.358	In Control
4664	0.425	In Control	4741	0.301	In Control
4665	0.433	In Control	4742	0.386	In Control
4666	0.435	In Control	4743	0.178	In Control
4667	0.040	In Control	4744	0.058	In Control
4668	0.006	In Control	4745	0.139	In Control
4669	0.037	In Control	4746	0.017	In Control
4670	0.036	In Control	4763	0.258	In Control
4671	0.046	In Control	4764	0.002	In Control
4672	0.325	In Control	4765	0.106	In Control
4673	0.115	In Control	4766	0.810	Out of Control
4674	0.376	In Control	4767	0.073	In Control
4675	0.064	In Control	4768	0.531	In Control
4676	0.034	In Control	4769	0.220	In Control
4677	0.166	In Control	4770	0.313	In Control
4678	0.058	In Control	4771	0.179	In Control
4679	0.154	In Control	4772	0.049	In Control
4680	0.325	In Control	4773	0.125	In Control
4681	0.147	In Control	4774	0.067	In Control
4682	0.167	In Control	4775	0.165	In Control
4725	0.400	In Control	4776	0.161	In Control
4726	0.053	In Control	4777	0.117	In Control

F. INDIVIDUAL AND MOVING RANGES MEASUREMENTS FOR MOSITURE CONTENT

Roll #	*X*	*R*	Roll #	*X*	*R*
4657	5.000		4727	4.617	0.078
4658	5.067	0.067	4728	5.450	0.834
4659	5.093	0.026	4729	5.467	0.016
4660	5.125	0.032	4730	5.058	0.408
4661	5.150	0.025	4731	4.108	0.950
4662	4.992	0.158	4734	4.317	0.208
4663	4.950	0.042	4740	4.674	0.358
4664	4.525	0.425	4741	4.975	0.301
4665	4.092	0.433	4742	4.589	0.386
4666	4.526	0.435	4743	4.767	0.178
4667	4.567	0.040	4744	4.750	0.017
4668	4.563	0.004	4745	4.800	0.050
4669	4.600	0.037	4746	4.817	0.017
4670	4.617	0.017	4763	4.558	0.258
4671	4.583	0.033	4764	4.558	0.000
4672	4.908	0.325	4765	4.533	0.025
4673	4.959	0.051	4766	5.343	0.810
4674	4.583	0.376	4767	5.417	0.073
4675	4.562	0.021	4768	4.886	0.531
4676	4.575	0.013	4769	5.033	0.147
4677	4.550	0.025	4770	5.317	0.283
4678	4.492	0.058	4771	5.258	0.059
4679	4.583	0.092	4772	5.208	0.049
4680	4.258	0.325	4773	5.333	0.125
4681	4.225	0.033	4774	5.267	0.067
4682	4.192	0.033	4775	5.201	0.066
4725	4.592	0.400	4776	5.258	0.058
4726	4.539	0.053	4777	5.142	0.117

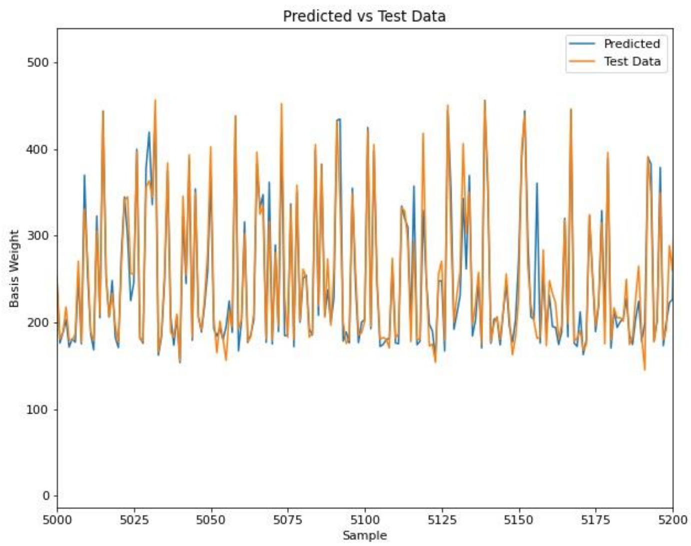
G. CONTROL SITUATION IN LC-240 PAPER MOISTURE CONTENT FOR ICC

Roll #	Individual Value (X)	Status	Roll #	Individual Value (X)	Status
4657	5.000	In Control	4727	4.617	In Control
4658	5.067	In Control	4728	5.450	Out of Control
4659	5.093	In Control	4729	5.467	Out of Control
4660	5.125	In Control	4730	5.058	In Control
4661	5.150	In Control	4731	4.108	Out of Control
4662	4.992	In Control	4734	4.317	Out of Control
4663	4.950	In Control	4740	4.674	In Control
4664	4.525	In Control	4741	4.975	In Control
4665	4.092	Out of Control	4742	4.589	In Control
4666	4.526	In Control	4743	4.767	In Control
4667	4.567	In Control	4744	4.750	In Control
4668	4.563	In Control	4745	4.800	In Control
4669	4.600	In Control	4746	4.817	In Control
4670	4.617	In Control	4763	4.558	In Control
4671	4.583	In Control	4764	4.558	In Control
4672	4.908	In Control	4765	4.533	In Control
4673	4.959	In Control	4766	5.343	Out of Control
4674	4.583	In Control	4767	5.417	Out of Control
4675	4.562	In Control	4768	4.886	In Control
4676	4.575	In Control	4769	5.033	In Control
4677	4.550	In Control	4770	5.317	Out of Control
4678	4.492	In Control	4771	5.258	In Control
4679	4.583	In Control	4772	5.208	In Control
4680	4.258	Out of Control	4773	5.333	Out of Control
4681	4.225	Out of Control	4774	5.267	In Control
4682	4.192	Out of Control	4775	5.201	In Control
4725	4.592	In Control	4776	5.258	In Control
4726	4.539	In Control	4777	5.142	In Control

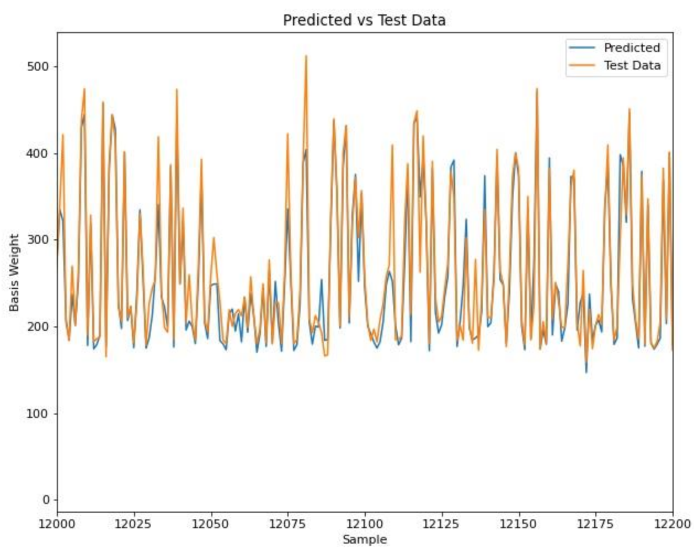
H. CONTROL SITUATION IN LC-240 PAPER MOISTURE CONTENT FOR IMRCC

Roll #	Range Value (*MR*)	Status	Roll #	Range Value (*MR*)	Status
4657		In Control	4727	0.078	In Control
4658	0.067	In Control	4728	0.834	Out of Control
4659	0.026	In Control	4729	0.016	In Control
4660	0.032	In Control	4730	0.408	In Control
4661	0.025	In Control	4731	0.950	Out of Control
4662	0.158	In Control	4734	0.208	In Control
4663	0.042	In Control	4740	0.358	In Control
4664	0.425	In Control	4741	0.301	In Control
4665	0.433	In Control	4742	0.386	In Control
4666	0.435	In Control	4743	0.178	In Control
4667	0.040	In Control	4744	0.017	In Control
4668	0.004	In Control	4745	0.050	In Control
4669	0.037	In Control	4746	0.017	In Control
4670	0.017	In Control	4763	0.258	In Control
4671	0.033	In Control	4764	0.000	Out of Control
4672	0.325	In Control	4765	0.025	In Control
4673	0.051	In Control	4766	0.810	Out of Control
4674	0.376	In Control	4767	0.073	In Control
4675	0.021	In Control	4768	0.531	In Control
4676	0.013	In Control	4769	0.147	In Control
4677	0.025	In Control	4770	0.283	In Control
4678	0.058	In Control	4771	0.059	In Control
4679	0.092	In Control	4772	0.049	In Control
4680	0.325	In Control	4773	0.125	In Control
4681	0.033	In Control	4774	0.067	In Control
4682	0.033	In Control	4775	0.066	In Control
4725	0.400	In Control	4776	0.058	In Control
4726	0.053	In Control	4777	0.117	In Control

I. PREDICTED VS. TEST DATA FOR TWO DIFFERENT SAMPLES RANGES.



a) Model performance: predicted vs test with samples from 5000 to 5200



b) Model performance: predicted vs test with samples from 12000 to 12200

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