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A Goal Programming-Monte Carlo Simulation Methodology for Modeling Process Quality Control

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Abstract
Quality profiling seeks to know the quality characteristics of products and processes to improve customer satisfaction and business competitiveness. It is required to develop new techniques and tools that upgrade and complement the traditional analysis of process variables. This article proposes a new methodology to model quality control of the process and product quality characteristics by applying optimization and simulation tools. The application in the production process of carbonated beverages allowed us to identify the most influential variables on the gas content and the degrees Brix of beverage.

Keywords
Goal programming; Monte Carlo simulation; Process optimization and simulation; Process quality profiling; Quality control modeling.

Introduction

Quality profiling consists of identifying key inputs and outputs of the process, collecting data about the behavior of the variables and the product quality characteristics, and analyzing the interrelationships. Quality profiling allows estimating the result of the product quality characteristics from known information about the process variables values. The main objective of quality profiling is to obtain mathematical models that facilitate decision-making in process monitoring and improving product quality.

Goal Programming (GP) was proposed by Charnes and Cooper, as a derivation of linear programming (Aouni & Kettani, 2001). Although GP aimed to solve industrial problems, it has expanded with applications in areas such as economics, agriculture, and environmental resources. Today, GP is one of the most popular multi-criteria approaches for solving complex, large-scale problems.

The last 40 years have been a transformative era in the progress of new methodologies to help decision-making, especially for developing multi-criteria decisions and GP. Thus, GP is one of the best-known tools that support a wide network of researchers and professionals who continuously feed it with theoretical developments and applications (Aouni & Kettani, 2001).

Decision-making is a complex issue in process management. Aouni and Kettani (2001) state that the development of technological environments allows stakeholders to make collective decisions by formalizing procedures for process quality control using optimization and simulation tools.

Schniederjans and Karuppan (1995) developed a zero-one GP model to select the best quality control tools for simultaneously optimizing various process quality characteristics. In these cases, the response variables may differ in many properties as scale, measurement unit, and optimization type.

Uncertainty in perception of both priorities of the objectives and their economic and environmental scale can generate difficulties in making management decisions. Therefore, Chang and Wang (1997) applied a fuzzy goal programming (FGP) approach for optimal planning of solid waste management systems. The fuzzy decision-maker goals are quantified by using specific membership functions in several types of management alternatives for solid waste. Aouni et al. (2009) stated that fuzziness is related to the nature of the goals involved in managerial decision-making.

There are different approaches for modeling and building optimization problems (Kazemzadeh et al., 2008; Alazemi et al., 2022; Amorim et al., 2022). An example is production scheduling in mining for mix-

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ing raw materials before concentration. Thus, Zhang et al. (1993) developed and applied a variable target scheduling model for short and medium-term open pit planning for a large-area coal mine. Chanda and Dagdelen (1995) stated that it is necessary to implement a linear objective programming model in short-term mine planning to achieve better results.

Optimal experimental designs aimed to predict variance and improve performance. Optimal experimental designs have been applied in quality management to improve products management. Ozdemir (2021) proposed a lexicographic GP model by incorporating the i-optimal experimental design to find controllable factors. In water supply management, Musa (2020) developed a multi-target model to meet growing demands across multiple sectors in Saudi Arabia. The model allowed to forecast the supply and demand of water from 2020 to 2050.

Frequently, identifying variables and control factors in industrial processes is quite complex. Nuriani and Gunawan (2020) applied response surface methodology and GP to find the optimal combination of quality characteristics in coconut oil production. Gholizadeh and Tajdin (2019) developed a GP model with statistical quality control to improve the process capability indices of different quality characteristics. It reduced waste and the cost of the finished product and improved customer satisfaction.

Quality function deployment (QFD) allows for the achievement of various objectives simultaneously. It is complex for decision-makers to establish the final value of each target in unknown and uncertain environments. Thus, Delice and Zülal (2013) proposed a fuzzy programming model to determine a combination of optimal values by comparing the effective alternatives of product design and its easy and fast development.

In addition, GP has been integrated with Design of Experiments (DOE) to identify optimal levels of process control in several areas. Gijo and Ravindran (2008) conducted a full-factorial experiment with two factors at three levels each and used GP to optimize the two response variables of a concrete mixture. Wang et al. (2016) combined chance-constrained programming and GP to optimize the risk adjustable in power system scheduling.

İç et al. (2022) determined critical variables of gas metal arc welding and optimized the process performance by integrating a full-factorial design, regression analysis, and GP. Tansel Iç et al. (2022) combined a 2^k DOE and GP to determine variables optimum levels of a flexible manufacturing cell considering multiobjective performance.

Despite the previous works, there is a gap in developing and implementing flexible models that integrate optimization and simulation tools for solving complex problems of process and product quality profiling. Hence, this paper develops a process quality profiling methodology by integrating GP to determine the optimal levels of the process variables and Monte Carlo Simulation (MCS) to estimate the variability of the quality characteristics of the product. The methodology is implemented in a carbonated beverage production process.

The main contribution of this paper is developing a flexible modeling methodology that integrates optimization and simulation tools to solve complex engineering problems. So, it is possible to predict the behavior of the quality characteristics and then, eliminate or reduce deviations from meeting target specifications and improve making decisions in process management.

Goal Programming (GP)

The standard GP model considers the priority of goals to be precise and deterministic. However, a typical quality control profiling problem is fixing the levels of input process parameters to meet a required output specification. In particular, when the product has several quality characteristics that have to satisfy different specifications (Zhang et al., 1993).

Therefore, it is necessary to establish a reference procedure to formulate a GP model, considering the following:

1. Set the $f(x)$ goals (attributes) from least to most important.
2. Determine the importance level (Y_n) of each goal.
3. Goal Definition (negative deviation variable, δ^-, and/or positive deviation variable, δ^+).

The decision space (Y') is the set of values vectors that reach the different attributes in each object:

$$Y' = f(x) + \delta^- - \delta^+. \tag{1}$$

In general, the i-th goal attribute (Y_n) is given by:

$$Y_n = f(x) + \delta_n^- - \delta_n^+. \tag{2}$$

The target space is determined by the set $f(s) = \{f_1(x), \ldots, f_p(x)|\ x \in S\}$, $S \subseteq R^N$, $S \neq \varphi$, $f_j : S \to R$, $j \in \{1, \ldots, p\}$. The multi-objective optimization problem is propound as:

$$\begin{aligned} &\min\,(f_i(x), \ldots, f_p(x)) \\ &s.t.:\ \ x \in S. \end{aligned} \tag{3}$$

Obtaining an optimal solution in $\bar{x}^j$, with an optimal value in f_j^*.

Thereby, it is possible to obtain the following GP solution types: ideal, efficient, weakly efficient, preferred, utility function, satisfactory, or compromise. Due to the characteristics of this work, it is of interest to obtain a satisfactory solution.

GP and modeling process quality control

Output variables in a quality control model correspond to product specifications and meeting the quality characteristics of a product depends on input and process variables performance (Valdés-Manuel & Cogollo-Flórez, 2022). Therefore, it is necessary to determine the operating range of each input and process variable.

The main issue in quality control modeling is to find a solution with optimal values of input and process variables that meet all the product specifications, subject to some constraints. When there is no single optimum, the best solution is in the set of feasible solutions (Cherif et al., 2008).

Multiple and conflicting objectives in quality control modeling lead to efficient rather than optimal solutions. Those are in the domain of feasible solutions, such that meeting one objective affects at least one other; that is, there are possible compromises between the objectives (Mohammed & Hordofa, 2016). Thus, the decision maker must use an appropriate method and select a more preferred and efficient solution, known as the best compromise solution (Belhoul et al., 2014).

Let $R_1 \ldots, R_l$ be the l input variables, $x_1, \ldots, x_k$ the k process variables and $Y_1, \ldots, Y_r$ the r output variables. The linear relationship between the variables is:

$$Y_i = Q_i\left(R_1, \ldots, R_l; x_1, \ldots, x_k\right) \quad \text{for} \quad i = 1, 2, \ldots, r, \tag{4}$$

where Q is the linear function.

Formulating the quality control problem as a GP model requires modifying the specifications form and setting of the regression equation (Sengupta, 1981). Modifying the specifications form is made from a two-sided specification to an upper single-sided specification (USL) by transforming the respective variable and subtracting its lower specification limit (LSL):

$$x_k = x_i - \text{LSL} \leq (\text{USL} - \text{LSL}). \tag{5}$$

The regression equation is refitted by rewriting (4) as:

$$Y_1' = Q_i'\left(R_1', \ldots, R_l';\ x_1', \ldots, x_k'\right), \tag{6}$$

where Y_1', R_l' and x_k' are the modified variables. Thus, the refitted regression equation is:

$$Y_n' = C + R' + x_1' - x_2' + x_3' + \ldots + x_m', \tag{7}$$

where C is the fitting coefficient.

The optimization problem can be expressed as follows: For $i = 1, 2, \ldots, r$, find the values of x_m' and R' such that Y_i' meets the specifications considering the constrains within their operating range on the values of $R_1', \ldots, R_l'$ and $x_1', \ldots, x_k'$.

Thereby, the problem was reduced to minimize the sum of the deviation variables from the goal subject to the constrains, considering the factors priority. So, the general process control problem is formulated as a lexicographic GP problem (Sengupta, 1981):

$$\min \sum_{m=1}^{lkr} \left(\delta_m^+ + \delta_m^-\right) \tag{8a}$$

$$\min P_{Y_i} \sum_{i=0}^{r} \left(\delta_{Y'}^+ + \delta_{Y'}^-\right) + P_{X_k} \sum_{j=0}^{r} \left(\delta_{Y'}^+ + \delta_{Y'}^-\right) + P_{D_i} \sum_{t=0}^{r} \left(\delta_{Y'}^+ + \delta_{Y'}^-\right). \tag{8b}$$

Subject to:

$$D_i' + \delta_{D_i'}^- - \delta_{D_i'}^+ = z_{D_i}' \quad (\text{for} \quad i = 1, 2, \ldots, r), \tag{8c}$$

$$x_j' + \delta_{x_j'}^- - \delta_{x_j'}^+ = z_{x_j}' \quad (\text{for} \quad i = 1, 2, \ldots, r), \tag{8d}$$

$$Y_i' + \delta_{Y_i}^- - \delta_{Y_i}^+ = z_{Y_i}' \quad (\text{for} \quad i = 1, 2, \ldots, r), \tag{8e}$$

$$Y_i', \ x_j' \ \text{ and } \ D_i' \geq 0,$$

where (8c) is the input goal constrain, (8d) is the process goal constrain, (8e) is the output goal constrain, P_{Y_i}, P_{X_i} and P_{R_i} are the priority factors, z_{Y_i}', z_{x_j}' and z_{R_i}' are the modified specification limits.

For one-side solutions, only the positive or negative deviance variables will exist and for "close to" specifications both deviance must be considered (Cherif et al., 2008).

Monte Carlo simulation (MCS)

The simulation principle is based on the logical-mathematical model construction of the system or the decision processes to assist in strategic decision-making. One of the essential considerations in simulation processes is the probability distribution identification that best fits the data set.

The main objective of the simulation is to duplicate the process characteristics and behaviors and to imitate the operation by mathematical modeling. Multiple Probability Simulation (MPS) or Monte Carlo Simulation (MCS) is a mathematical technique for estimating the possible outcomes of an event (Salazar & Alzate, 2018) that allows evaluating the behavior of the incident variables within the analyzed problem to know the uncertain behavior.

MCS is based on the differential principle that increases as a function of the desired accuracy allowing predict the results further in time with greater precision. Regardless of the tool used, the MCS consists of three basic steps:

1. Set up the predictive model.
2. Consider historical data to define a range of probable values to specify the probability distributions of the independent variables (X_n).
3. Run simulations repeatedly.

The MCS methodology applies to various research areas since it provides optimal solutions to various mathematical problems, allowing experimentation with samples. Thus, simulation involves generating an artificial history of the system and monitoring this history through experimental manipulation. In addition, it helps to infer the operating characteristics of the system (Salazar & Alzate, 2018).

Jacobs and Chase (2021) state the MCS reproduces the values of a variable from its behavior based on the selection of random numbers. Therefore, the application of MCS requires having enough historical information to establish the behavior of the variables and how they affect or are affected by other variables.

MCS provides advantages to predictive models with fixed inputs, such as calculating input correlations or performing sensitivity analysis. MCS has been applied to analyze diverse real-life scenarios, such as project management, sales forecasting, pricing, and even Artificial Intelligence (Ji & AbouRizk, 2018).

GP-MCS methodology

The Goal Programming – Monte Carlo Simulation (GP-MCS) methodology for modeling process quality control has two main stages with their respective steps (Fig. 1). The GP-MCS methodology was applied in a carbonated beverage bottler located in the city of Medellin (Colombia) and the results are detailed in the following section.

Results

Results stage 1: Goal programming

Multiple regression analysis and description of model variables

Carbon dioxide and syrup are the two main raw materials for producing carbonated beverages and they are responsible for astringency and flavor, respectively. The amount of Brix degrees of the syrup is the input variable considered for this study. The two main quality characteristics of carbonated beverages are the carbon dioxide content and the Brix degrees.

All variables are controllable and can be directly measured. The input variable is the sugar concentration of the syrup, measured as degrees Brix (°Bx). The process variables are the beverage temperature in the carbo-cooler (°C), the beverage temperature in the filler (°C), the filler speed (bottles per minute - BPM), and the refrigerant suction pressure (PSI). The output variables correspond to two quality characteristics of the finished product: the gas content in the beverage (CO_2 volumes) and the Brix degrees of the beverage (°Bx). Details of input and process variables and quality characteristics are in Table 1.

For the multiple linear regression analysis, a process capability study was carried out by randomly

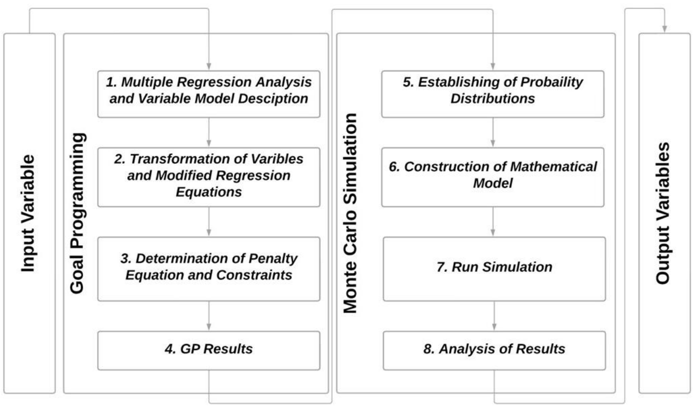

Fig. 1. The GP-MCS Methodology stages (Own work)

Table 1
Description of Model Variables (own work)

Variable Type	Variable	Target
Input Variable	(D) Degrees Brix of Syrup (%)	[55.13, 55.33]
Process Variables	(x_1) Carbo-Cooler Temperature (°C)	[0, 2]
	(x_2) Filler Temperature (°C)	[2, 4]
	(x_3) Filler Speed (BPM)	[530, 550]
	(x_4) Refrigerant Suction Pressure (PSI)	[43, 47]
Output Variable	(Y_1) Gas Content (Volumes of CO_2)	[3.70, 4.00]
	(Y_2) Degrees Brix of Drink (%)	[10.35, 10.55]

selecting thirty samples of size four. The models assumptions of linearity, independence, homoscedasticity, normality, and non-collinearity were validated by calculating the correlation coefficient, the Durbin-Watson statistic, the Levene statistic, the Anderson-Darling statistic, and the variance inflation factor, respectively. The matrix with the respective correlation coefficients between the variables is shown in Table 2.

Table 2
Correlation matrix (own work)

Origin variable	Destination variable	Correlation coefficient
x_1	x_2	0.1961
x_1	x_3	–0.2633
x_1	x_4	–0.0808
x_1	D	0.0111
x_1	Y_1	0.3353
x_1	Y_2	–0.3911
x_2	x_3	0.0214
x_2	x_4	–0.0605
x_2	D	0.1147
x_2	Y_1	0.0535
x_2	Y_2	–0.3740
x_3	x_4	0.1070
x_3	D	–0.1598
x_3	Y_1	0.0504
x_3	Y_2	0.1328
x_4	R	0.1454
x_4	Y_1	–0.1907
x_4	Y_2	0.1110
D	Y_1	0.1468
D	Y_2	0.4540
Y_1	Y_2	–0.2133

Thus, the following relationships were obtained:

$$Y_1 = -17.0745 + 0.3449D + 0.1009x_1 - 0.0132x_2 + 0.0038x_3 - 0.0057x_4\,, \quad (9)$$

$$Y_2 = -7.8798 + 0.3313D - 0.0423x_1 - 0.0464x_2 + 0.0003x_3 + 0.0027x_4\,. \quad (10)$$

In addition, Table 2 shows the results of the correlation coefficients between the input variable and the process variables.

Transformation of variables and modified regression equations

Transformation of variables to obtain one-side specifications and modify the constant terms in the regression equations according to (5) is shown from (11) to (17):

$$D' = D - 55.13 \le 0.2, \quad (11)$$

$$x_1' = x_1 - \le 2, \quad (12)$$

$$x_2' = x_2 - 2 \le 2, \quad (13)$$

$$x_3' = x_3 - 530 \le 20, \quad (14)$$

$$x_4' = x_4 - 43 \le 4, \quad (15)$$

$$Y_1' = Y_1 - 3.70 \le 0.30, \quad (16)$$

$$Y_2' = Y_2 - 10.35 \le 0.20. \quad (17)$$

Then, the modified regression equations applying (7) are the following:

$$Y_1' = 2.7702 + 0.3449D' + 0.1009x_1' - 0.0132x_2' + 0.0038x_3' - 0.0057x_4'\,, \quad (18)$$

$$Y_2' = 9.9032 + 0.3312D' - 0.0423x_1' - 0.0464x_2' + 0.0003x_3' + 0.0027x_4'\,. \quad (19)$$

Determination of penalty equation and constraints

The minimization of the GP problem can be formulated as follows:

$$\begin{aligned} \min z:\ & P_{Y_1}\left(\delta_{Y_1}^- + \delta_{Y_1}^+\right) + P_{Y_2}\left(\delta_{Y_2}^- + \delta_{Y_2}^+\right) \\ & + P_{x_1}\left(\delta_{x_1}^- + \delta_{x_1}^+\right) + P_{x_2}\left(\delta_{x_2}^- + \delta_{x_2}^+\right) \\ & + P_{x_3}\left(\delta_{x_3}^- + \delta_{x_3}^+\right) + P_{x_4}\left(\delta_{x_4}^- + \delta_{x_4}^+\right) \\ & + P_D\left(\delta_D^- + \delta_D^+\right). \end{aligned} \quad (20)$$

Subject to:

Input constraint:

$$D' + \delta_D^- - \delta_D^+ = 0.2. \quad (21)$$

Process constraints:

$$x_1' + \delta_{x_1}^- - \delta_{x_1}^+ = 2, \quad (22)$$

$$x_2' + \delta_{x_2}^- - \delta_{x_2}^- = 2, \quad (23)$$

$$x_3' + \delta_{x_3}^- - \delta_{x_3}^- = 20, \quad (24)$$

$$x_4' + \delta_{x_4}^- - \delta_{x_4}^- = 4 \quad (25)$$

with: $\geq D \leq 2, x_t' \geq 0, t = [1, 2, 3, 4]$.

Output constraints:

$$Y_1' + \delta_{Y_1}^- - \delta_{Y_1}^+ = 4; \quad i.e.$$

$$\begin{aligned} & 0.3449D' + 0.1009x_1' - 0.0132x_2' \\ & \quad - 0.0038x_3' - 0.0057x_4' = 0.3196, \end{aligned} \quad (26)$$

$$\begin{aligned} & 0.3313D' - 0.0423x_1' - 0.0464x_2' \\ & \quad + 0.0038x_3' + 0.0027x_4' = 0.6468. \end{aligned} \quad (27)$$

The constrain (22) guarantees the fulfillment with the carbo – cooler temperature target, (23) guarantees fulfilling with the filler temperature target, (24) guarantees to fulfill with the filler speed target, and (25) guarantees the fulfillment with the refrigerant suction pressure target.

Solving the Lexicographic GP problem described in (20), the optimal solution to guarantee the process capability to meet the target specifications of the response variables is D =55.23, x_1 =1, x_2 =2, x_3 =530 and $x_4 = 43$. Moreover, the positive (δ^+) and negative (δ^-) deviations of the response variables are equal to zero and there is a satisfactory solution in $Y_1 = 3.85$ and $Y_2 = 10.45$.

Results Stage 2: Monte Carlo simulation

The results of the stage 1 became in inputs of the stage 2 (MCS). Thus, the multiple regression equations obtained in (9) and (10) are used as the mathematical models for running the MCS.

Establishing of probability distributions

The parameters and probability distributions of the input and process variables were selected from the initial process capability study. Goodness-of-fit tests were performed and the Anderson-Darling (AD) statistic, with a significance level of 0.05, was used to select the distribution that best fits the data for each variable (Table 3).

Table 3
Probabilistic Distributions (own work)

Variable	Type of distribution	Parameters
D	Normal (N)	(55.22; 0.1)
x_1	Rayleigh (R)	(1.01; 0.15)
X_2	Exponential (E)	(4.38; 0.07)
X_3	Beta (B)	(1.15; 0.64; 530; 540)
x_4	Lognormal (LN)	(43; 0.04; 0.14)

Construction of mathematical model and run simulation

The mathematical models of the MCS are based on (9) and (10) and presented in (28) and (29). They consider the correlation coefficients between variables (Table 2) and the probabilistic distributions (Table 3). Next, 1000 simulation runs were performed.

$$\begin{aligned} Y_1 = & -17.0745 + 0.3449\{D \to N[55.22; 0.1]\} \\ & + 0.1009\{x_1 \to R[1.01; 0.15]\} \\ & - 0.0132\{x_2 \to E[4.38; 0.07]\} \\ & + 0.0038\{x_3 \to B[1.15; 0.64; 530; 540]\} \\ & - 0.0057\{x_4 \to LN[43; 0.04; 0.14]\}, \end{aligned} \quad (28)$$

$$\begin{aligned} Y_2 = & -7.8798 + 0.3313\{D \to N[55.22; 0.1]\} \\ & - 0.0423\{x_1 \to R[1.01; 0.15]\} \\ & - 0.0464\{x_2 \to E[4.38; 0.07]\} \\ & + 0.0003\{x_3 \to B[1.15; 0.64; 530; 540]\} \\ & + 0.0027\{x_4 \to LN[43; 0.04; 0.14]\}. \end{aligned} \quad (29)$$

Fig. 2 and Fig. 3 show the histograms of simulation results for gas content and degrees Brix, respectively. The selected reliability percentage for the confidence intervals is 95%. Thereby, there is a 95% probability that the beverage gas volumes are between 3.76 and 3.95 and that the Brix degrees are between 10.37 and 10.56.

These ranges contain the target specifications of 3.85 and 10.45 for gas and Brix, respectively. Furthermore, it was possible to determine the capability to

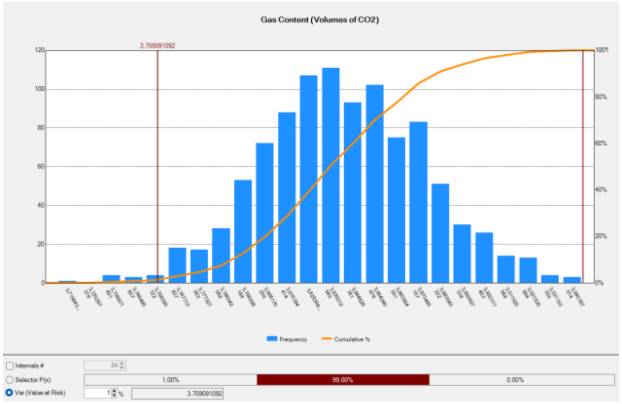

Fig. 2. Histogram of simulation results for gas content (own work)

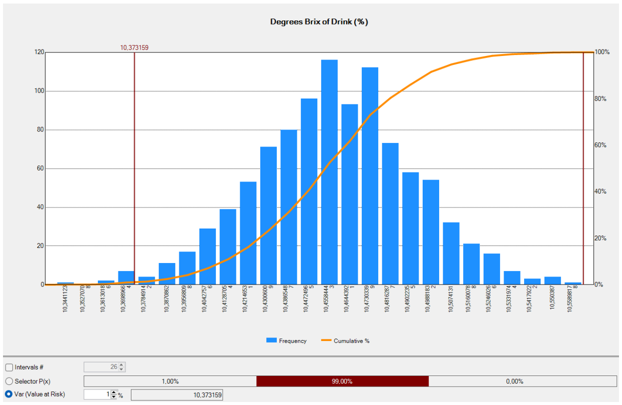

Fig. 3. Histogram of simulation results for degrees Brix (own work)

consistently meet the specifications through interval estimation of the centered capability ratio, C_{pk}. Thus, the C_{pk} estimate for gas is 1.34, ranging from 1.16 to 1.52, and the C_{pk} estimate for Brix is 0.89, ranging from 0.76 to 1.02.

A sensitivity analysis was performed to predict the optimal results of the response variables, Y_1 and Y_2, considering uncertainty conditions and using the Pearson ratio coefficient as the statistic for determining the strength of the relationship between the variables (Fig. 4 and Fig. 5).

Fig. 4 shows that the most influential variables on the gas content are the degrees Brix of syrup and the degrees Brix of drink. Fig. 5 shows that the degrees Brix of syrup and the gas content are the variables that have the highest impact on the degrees Brix of drink.

Also, all variables are relevant for implementing the GP-MCS methodology proposed in this work. However, some variables generate a higher impact on the product quality characteristics and compliance with specifications. So, it is possible to make better decisions for process improvement based on the scenario analysis regarding the uncertain behavior of the process variables.

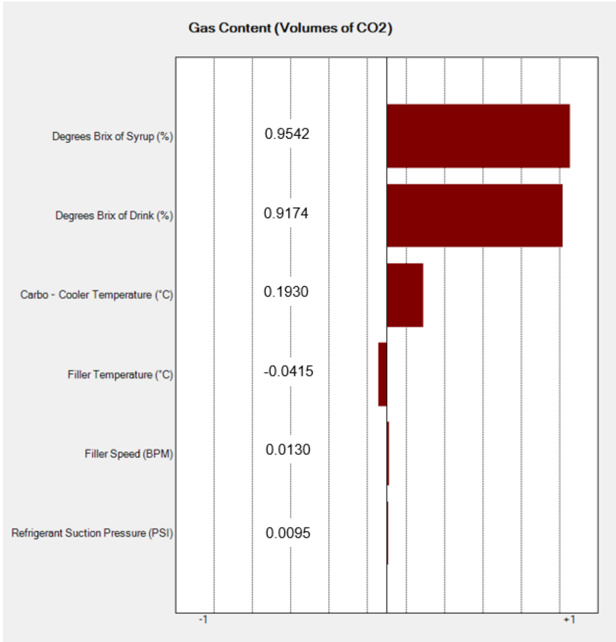

Fig. 4. Pearson sensitivity analysis for gas content (own work)

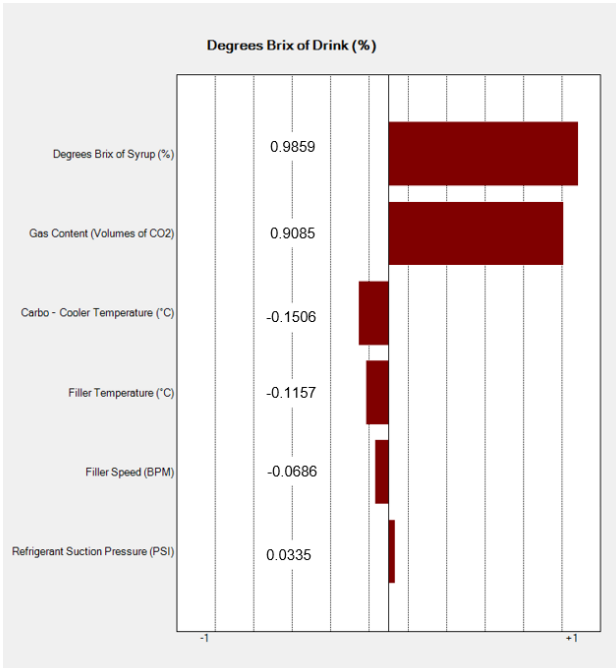

Fig. 5. Pearson sensitivity analysis for degrees Brix (own work)

Conclusions

GP provides higher flexibility in process modeling and optimization when there are many variations of constraints and goal priorities in multi-objective problems. MCS allows treating uncertainty and performing risk analysis by creating new models of possible outcomes by permuting a range of values.

This GP-MCS methodology is a novel approach in quality control profiling and allows performing a full mapping of the optimal operating ranges of the process and response variables. Moreover, it is possible to probabilistically estimate the process capability for meeting multiple quality characteristics. The GP-MCS methodology has a generalized approach that allows its application in other types of industrial processes or services.

The main contribution of this work is the implementation of a lexicographic model using optimization and simulation tools for solving complex product and process quality profiling problems. This issue is a relevant research avenue in Quality Engineering in the current context of the fourth industrial revolution.

Future work will focus on the application of the tool in other business sectors and the integration of multi-objective optimization and artificial intelligence tools.

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