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Analyzing Process Quality Control Variables Using Fuzzy Cognitive Maps

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Abstract
Meeting quality characteristics of products and processes is an important issue for customer satisfaction and business competitiveness. It is necessary to integrate new techniques and tools that improve and complement traditional process variables analysis. This paper proposes a new methodological approach to analyze process quality control variables using Fuzzy Cognitive Maps. Application of the methodology in the production process of carbonated beverages allowed identifying process variables with the greatest influence on finished product quality. The process variables with the greatest impact on carbon dioxide content in the beverage were the beverage temperature in the filler, the carbo-cooler pressure, and the filler pressure.

Keywords
Fuzzy Cognitive Maps, Process management and improvement, Process variables control, Quality control, Soft computing applications.

Introduction

Production Management of goods or services involves a series of control and planning actions to ensure compliance with the operating conditions of the process that influence the finished product quality. Regardless of the complexity of the production system, it is necessary to identify the variables and factors that determine the product quality and the operation levels that guarantee uniformity and compliance with the design specifications or those agreed with the client.

Quality control still plays an important function in the quality assurance of products and processes, regardless of technological advances in production systems. Moreover, quality control models can fail when they do not consider uncertainty and interrelationships between process variables. This can lead to finished product quality issues such as frequent product recalls due to failures in the quality function in production or some other stage of the product life cycle (Flynn & Zhao, 2015).

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Traditionally, the analysis of process quality control variables is carried out by applying tools and techniques of industrial statistics, such as descriptive analysis, control charts, and process capability studies (Montgomery, 2019). The frequent changes and technological developments in computing tools create the need for incorporating new approaches to control products and processes.

Fuzzy Cognitive Maps (FCMs) are soft computing tools that have proven their adequate performance to analyze the interrelationships between variables in processes. FCMs are a combination of fuzzy logic and neural networks, which are graphical representations used to illustrate causal reasoning with a structure that allows backward or forward progress and performing direct and inverse correlation analysis between related events (Dickerson & Kosko, 1994).

FCMs have been applied in areas such as medicine, administration, and automotive production, among others. The FCMs applications have proven to be effective as a tool for control, analysis, and decision-making (Papageorgiou, 2014). However, there is still little evidence of the FCMs application in the analysis of process quality control variables.

Despite some contributions to FCM applications in process analysis, there is a lack of research in the area. Therefore, this paper works on the lack of quality control methodologies using advanced modeling techniques that overcome the traditional descriptive statistical techniques. More modeling methodologies are needed to explain the behavior of the process variables and to predict future states.

Based on the above and aimed to propose new approaches that facilitate the process analysis to meet quality requirements and contribute to decision-making in process management, this paper develops a methodology for analyzing the process quality control variables using FCMs. The proposed methodology was applied in a carbonated beverage production process and allowed the identification of variables with the greatest influence on the finished product quality.

This work differs from previous ones in that it proposes a new approach to analyze process quality control variables, integrating soft computing tools. The integration of quality control and soft computing has not been widely studied and constitutes a research avenue.

The article is organized as follows: next section describes general aspects of the FCMs and the beverage carbonation process. Then, the steps of the methodology are shown and subsequently the results are detailed. Lastly, the conclusions are presented.

Literature review

This section shows the theoretical foundations of FCMs and some previous works where they have been applied for process analysis. Then, a general description of the beverage carbonation process is given.

Conceptualization of Fuzzy Cognitive Maps

FCMs are soft computing tools used to model and simulate systems in different study areas. The approach of FCMs is symbolic and allows modeling the behavior of any complex system in terms of interrelated concepts. Each concept represents an event, variable, or characteristic of the system (Kosko, 1986). The models represented using FCMs are easily understandable as they resemble the structure of human thought and constitute a tool for decision-making (Bourgani et al., 2013).

FCMs are neural network maps with interpretive features consisting of a set of concepts or nodes (neurons) and the causal relationships between them (Fig. 1) (Pelta & Cruz, 2018). The activation value of these relationships determines the interdependences strength and their impact on the network (model). The strength of the interrelationship between two nodes, C_i and C_j, is quantified by a numerical weight $w_{ij} \in [-1, +1]$ and is denoted by a causal weighted edge.

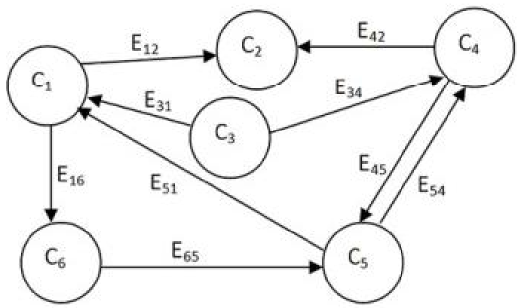

Fig. 1. A basic model of an FCM (own work)

Three kinds of causal relationships reflect the type of influence of one node on another in an FCM. If $w_{ij} > 0$, then C_i produces an increase in C_j with the absolute intensity of the weight $|w_{ij}|$. If $w_{ij} < 0$, then C_i produces a decrease in C_j with the corresponding absolute value of the intensity. If $w_{ij} = 0$, then there is no causal relationship between C_i and C_j.

Evaluating the FCM model validity to represent the studied system is carried out through an inference process. The parameters related to the inference process are the inference rule, the transfer function, and the detection criterion given by Kosko's activation rule (Pelta & Cruz, 2018):

$$A_i^{(k+1)} = f\left(A_i^k + \sum_{j=1}^{N} A_j^k \cdot w_{ji}\right), \quad j \neq k \tag{1}$$

where $A_i^{(k+1)}$ is a state vector representing the value of concept C_i at time $k+1$, A_i^k is the value of concept C_i at the previous time k, A_j^k is the value of C_j at time k, w_{ji} is the value of the cause-effect relationship between C_i and C_j, and $f(\cdot)$ refers to a monotonically non-decreasing and non-linear function used to set the activation value of each node in the interval $[0, 1]$:

$$f(A_i) = \frac{1}{1 + e^{-\lambda(A_i - h)}} \tag{2}$$

where λ is the sigmoid slope and h denotes the displacement. In some models, these parameters are closely related to the model convergence, making the predictions more reliable due to the model fit with the real system (Pelta & Cruz, 2018).

After the inference process, a FCM model can have three different behaviors: (i) The state vector may settle to some stationary vector reaching a fixed attractor point, (ii) The state vector may settle periodically to the same value, or (iii) The value of the state vector may change chaotically, which is called a chaotic attractor.

The ideal convergence behavior or the criterion for completion of the inference process depends on the type of system under analysis. For process and product improvement decisions, the model will be able to predict the future steady-state of the system. This is achieved when a fixed attractor point is used as the stopping criterion.

Applications of FCMs in process analysis

This section contains some previous studies related to the topic of interest of the paper, where FCMs are applied in process analysis. Yu and Hu (2010) developed an integrated framework for evaluating multiple production plants using FCMs and the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) strategy, considering the variables productivity, production quantity, production cost, and inventory quantity. Mls *et al.* (2017) applied FCMs for planning complex processes with uncertain and incomplete information, using evolutionary algorithms to improve production optimization results.

FCMs have been used to analyze plant and human operator efficiency, achieving a tool that facilitates managing resources and simultaneously, increasing the safety and reliability of the human operator (Kahraman & Yavuz, 2010). Also, integrated decision-making tools have been developed using FCMs for dynamic risk assessment in complex systems, considering the interdependence of risk factors (Jamshidi et al., 2018).

Hawer, Braun and Reinhart (2016) developed a FCM to select the appropriate combination of enablers that facilitate change in highly competitive production environments, allowing decision-makers to develop a cost-effective and dynamic factory design in the early planning stages. Vidal *et al.* (2015) applied a methodology to predict technological evolutions in green products using FCMs, to establish and quantify the relationship between eco-design strategies and technological evolution trends. This methodology identified the most ecological trends of design and development, so it could be useful for the prediction of technological forecasts in industries.

Konti and Damigos (2018) developed a collaborative FCM to determine the factors affecting biofuel production, considering factors such as a collection of organic material, financing of plants for processing organic material, and recycling policies. The most influential factor was the political factor since it directly influenced the other factors, which allowed them to focus their decision-making on the subject.

Peter, Antigoni and Vasileios (2015) modeled a wine production process by applying FCMs to determine the most influenced variables on the quantity and quality of the product. Harvest time, vineyard pruning, climate, and the amount of rainfall in the region were identified as relevant variables. FCMs have also been applied to model labor productivity, making it possible to control aspects such as absenteeism and low individual performance (Ahn et al, 2015).

Christova, Groumpos, and Stylios (2003) implemented FCMs to control the production plan of polyethylene terephthalate (PET), facilitating the execution of production under conditions of high uncertainty with unmeasured variables and undefined states. By modeling the process with FCMs, more uniformity was achieved in the follow-up and compliance with the production plan and schedule. Similarly, quality management in supply chains has been modeled using FCMs, identifying the percentage of the variable of rejects, returns, and defective products as those with the greatest impact on overall performance (Cogollo & Correa, 2018).

Yousefi and Tosarkani (2022) developed a methodology based on FCMs to identify and evaluate the main enablers of blockchain technology related to supply chain sustainability. It enabled significant improvement in supply chain performance, increasing traceability and transparency and helping managers to make the best decision in purchasing raw materials.

Rezaee et al. (2021) developed an intelligent strategy map applying FCM with a hybrid learning algorithm to establish key investment objectives in organizational projects. Alibage (2020) developed an FCM-based simulation model for safety intervention in the offshore oil industry. The model identified work design, communication, and human relations as the key factors for safety improvement.

Zanon et al. (2021) proposed a decision-making model based on gray FCM and fuzzy inference systems to analyze the causal relationship between organizational culture and supply chain efficiency. The model quantified the relationship between elements of cultural profile and firm performance through scenario simulation. Al-Gunaid et al. (2021) applied an FCM methodology to improve forecasting and measure factors affecting wheat crop yield. This made it possible to identify the factors to control and propose improvement strategies.

Bevilacqua et al. (2020) applied FCMs to analyze the domino effect in supply chains, obtaining information that allowed defining supply chain design strategies and developing a negotiation process guide to reduce sudden market change levels and improve mitigation measures. Yuan et al. (2020) developed a model based on FCM and kernel methods for time series forecasting. The experiments proved the outstanding performance of the combination of such methodologies, increasing the accuracy of the algorithms and the prediction speed.

The above works show that it is possible to apply FCMs for analyzing variables that influence the finished product quality in production process. Although the previous studies are not applied in specific cases in the quality control area, they are an important reference to this methodology, such as the variables treatment, the appropriate configuration of the FCM, and the analysis of simulation results.

Carbonated beverages process

Some basic concepts about carbonated beverages and its production process are mentioned in this section. Carbonated beverages are nonalcoholic, nonfermented beverages made by dissolving carbon dioxide (CO_2) in the water ready for direct human consumption, with or without the addition of natural or artificial sweeteners or both, fruit juices, fruit concentrates, and additives permitted by legislation (ICONTEC, 2020).

One of the main ingredients and the one in charge of giving the beverage main characteristic is CO_2, which is a colorless, slightly toxic, and odorless gas with a sour taste. It is a component of the air, although it is found in a very low percentage, formed by combustion and biological processes such as the decomposition of organic material, fermentation, and digestion (Berenguer & Bernal, 2000).

In the carbonation process, CO_2 is added to the beverage by using an equipment called carbo-cooler, applying CO_2 under pressure to the liquid, which must be kept at low temperatures (approximately 2°C) (Islas et al., 2015). CO_2 absorption is done through an operation known as gaseous absorption, where the gaseous mixture meets a liquid so that it absorbs one or more gas components (Eweis & Stiban, 2017).

Due to the above, beverage carbonation is a process that requires strict control of the variables that affect the main quality characteristic of the final product: the CO_2 content in the beverage. Thus, the development of a modeling methodology using FCMs contributes to the generation of knowledge in this area and becomes a fundamental contribution to the modeling of process quality by applying advanced computational techniques.

Materials and methods

The methodology used to analyze process quality control variables using fuzzy cognitive maps consists of five steps (Fig. 2). In the first stage, the model variables are defined, considering the process and output variables frequently monitored as part of the statistical quality control program. In the second stage, data on the behavior of the process variables are collected and a correlation analysis is carried out to determine the causal relationship weights. The obtained correlation matrix becomes the adjacency matrices as FCM model inputs.

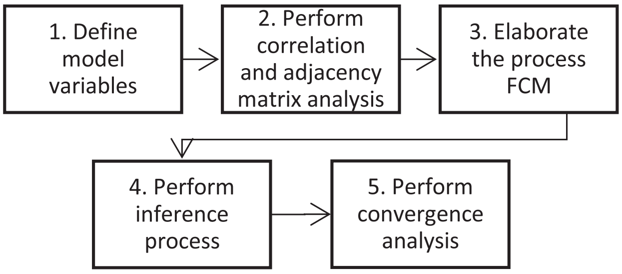

Fig. 2. The research methodology (own work)

In the third step, the fuzzy cognitive map of the carbonation process is elaborated. The model variables are grouped as a map and are linked using weighted arcs with the values of the adjacency matrix. In the fourth step, the actual dynamic behavior of the model is assessed by performing the inference process, applying (1) and (2). Finally, in the fifth step, the convergence analysis of the FCM is performed, by sorting the process variables that affect the response variable, according to the final value of its vectors.

Results

The following sections present the results after applying the methodology for analyzing the quality control variables of the carbonation process. The methodology was applied in a beverage company from Medellin (Colombia), whose name is omitted due to confidentiality commitments.

Definition of the process variables

Table 1 shows the variables of the carbonation process that influence the quality of the finished product. The variables are coded from C1 to C8 and the respective measurement units are shown.

Table 1
Carbonation process variables (own work)

ID	Variable	Measurement Unit
C1	CO_2 flow rate	Cubic feet per minute
C2	Carbo-cooler pressure	Pounds per square inch
C3	Refrigerant suction pressure	Pounds per square inch
C4	Beverage temperature in the carbo-cooler	Degrees Celsius
C5	Filler pressure	Pounds per square inch
C6	Beverage temperature in the filler	Degrees Celsius
C7	Filler speed	Bottles per minute
C8	Volume of CO_2 in the beverage	Volumes

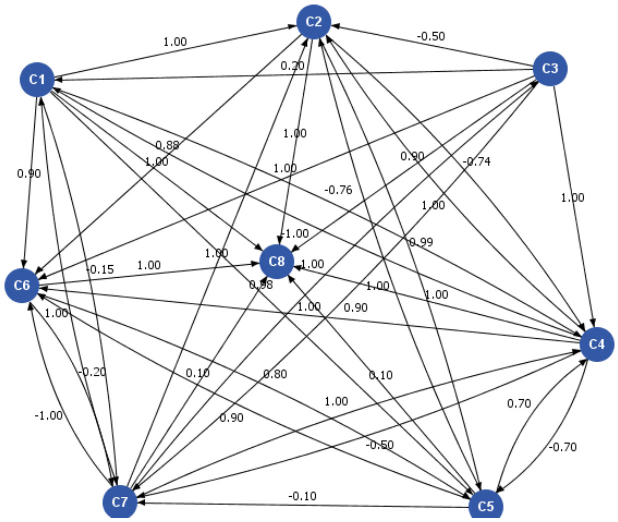

Fig. 3. The process FCM (own work)

Correlation and adjacency matrix analysis

For determining the values of the interrelationships between the model variables, data on the behavior of the process variables were collected through random sampling in a process capability study. Then, a multiple correlations analysis was carried out by considering the results of the variables measurement, obtaining the adjacency matrix shown in Table 2.

Table 2
Adjacency matrix (own work)

	C1	C2	C3	C4	C5	C6	C7	C8
C1	0	1	0	–0.76	0.98	0.90	–0.15	1
C2	0	0	0	–0.74	0.99	0.88	0	1
C3	0.20	–0.50	0	1	0	1	0.90	0.9
C4	–1	1	0	0	–0.70	1	–0.50	1
C5	0	1	0	0.70	0	0.9	–0.10	0.10
C6	0	0	0	0	0.8		–0.20	1
C7	1	1	1	1	0	–1	0	0.10
C8	0	0	0	0	0	0	0	0

Elaboration of the process FCM

Figure 3 shows the Fuzzy Cognitive Map (FCM) developed, representing the variables and weights of the interrelationships between them, based on the adjacency matrix (Table 2).

Table 3 shows the centrality values of the process variables represented in the FCM of Figure 3, which corresponds to the sum of the values of the incoming and outgoing arcs at each node (model variables). Centrality is a value that describes the significance of each node in the FCM. It is a measure of the strength of the model to represent the system under study and allows the identification of the process variables (ordinary) with the greatest impact on the response variable (receiver).

Table 3
Centrality of the process FCM (own work)

ID	Entries (a)	Outputs (b)	Centrality (c) $= a + b$	Type
C1	2.2	4.8	7.0	Ordinary
C2	4.5	3.6	8.1	Ordinary
C3	1	4.5	5.5	Ordinary
C4	4.2	5.2	9.4	Ordinary
C5	3.7	2.8	6.5	Ordinary
C6	5.7	2	7.7	Ordinary
C7	1.9	5.1	7.0	Ordinary
C8	5.1	0	5.1	Receiver

It is highlighted that the main variables of the process FCM (Fig. 3) are the beverage temperature in the carbo-cooler, the carbo-cooler pressure, and the beverage temperature in the filler. However, it is necessary to state that centrality is a static measure of the model construction to evaluate its congruence with the system, based on the data collected from the process. The identification and sorting of the process variables that really influence the quality of the product, are obtained after the inference process and convergence analysis, where the dynamic component of the interaction between the variables is incorporated.

Inference process

The inference process was developed by performing WHAT- IF simulations and Kosko's activation rule with own memory of (1), with the results visualized in Figure 4. It is noted that the variables converge rapidly to a steady-state, which is desired for the type of process under analysis. Due to the characteristics of the modeled process, the detection criterion was established at a fixed point or value, since this facilitates decision-making for product quality control.

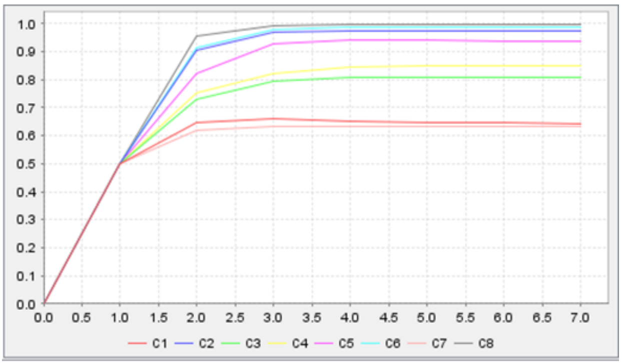

Fig. 4. Results of the inference process (own work)

Convergence analysis

Table 4 shows the values of the concepts (process variables) in the last step of the simulation and their descending sequence, which allows identifying the variables that most influence the process and the quality characteristic of the product (volume of CO_2 in the beverage). According to these results, it is noted that the final state vectors of the process variables converge to values above the significance threshold, which indicates that they all have an impact on the response variable, however, it is possible to identify three clearly distinct ranges of influence.

Table 4
Final sorting of the process variables (own work)

Order	Variable	Value
1	C8: Volume of CO_2 in the beverage	0.9952
2	C6: Beverage temperature in the filler	0.9865
3	C2: Carbo-cooler pressure	0.9743
4	C5: Filler pressure	0.9387
5	C4: Beverage temperature in the carbo-cooler	0.8506
6	C3: Refrigerant suction pressure	0.8089
7	C1: CO_2 flow rate	0.6433
8	C7: Filler speed	0.6339

In the first range are the variables that affect the response variable, these yielded the highest values: the beverage temperature in the filler (0.9865), the carbo-cooler pressure (0.9743), and the filler pressure (0.9367). This is consistent with the principles and theoretical references of the carbonation process (Islas et al., 2015).

Then, in the second range, two variables with high average influence are identified: the beverage temperature in the carbo-cooler (0.8506) and the refrigerant suction pressure (0.8089). Finally, there are variables with moderate influence: CO_2 flow rate (0.6433) and the filler speed (0.6339).

Conclusions

The rapid changes and developments in computational tools for modeling and simulation are a permanent challenge for quality management and control. Thus, the development of advanced analytical models is a growing research area. Because of the new demands of the global market for efficient production systems with high-quality levels, soft computing tools are perceived as one of the novel approaches to respond to the modeling of complex and highly uncertain processes.

This paper developed a methodology for analyzing process quality control variables based on Fuzzy Cognitive Maps, which demonstrated adequate performance through the application in a beverage carbonation process. From data obtained through sampling in a process capability study, it was found that the most influential variables to guarantee adequate CO_2 levels in the beverage were the beverage temperature in the filler, the carbo-cooler pressure, and the filler pressure.

The developed methodology constitutes a new approach to research process quality control, complementing the traditional studies that analyze indexes that reflect the degree of compliance with the target specifications. This methodology allows identifying the factors and variables that contribute to the variability and quantify their interrelationships, as a fundamental input for improved decision making.

This paper is a product of ongoing research whose main objective is to apply advanced modeling methods in the quality control of products and processes. The following phases will focus on developing a model that considers multiple stages of the production chain, the incorporation of statistical engineering techniques, and new learning algorithms.

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